PHD

# Taylor Rule Based Exchange Rate Models with Wealth Effects

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# Taylor Rule Based Exchange Rate Models with Wealth Effects

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# Abstract

This thesis focuses on the relationship between the exchange rate and its determinants using an endogenous monetary policy rule as represented by the Taylor rule. Compared to the recent literature on out-of-sample exchange rate predictability, I extend the model of Molodtsova and Papell (2009) by including two variables representing wealth effects, as has been suggested in the standard Taylor rule models. Using quarterly data from 1975-2008, I first investigate the econometric properties of the Taylor rule applied to U.K., Australian and Swedish data against the US dollar. Various unit root tests indicate that variables commonly used in such models are likely to be integrated of order one. However, by accounting for structural breaks, I can conclude that all variables are stationary. Parameter estimates suggest wealth effects are strongly related to the nominal exchange rates in these countries, in contrast to the standard monetary variables.

Furthermore, I evaluate short-horizon exchange rate predictability with the Taylor rule fundamentals model for the U.S. dollar against the Australian dollar, Swedish Krona and British Pound. Following the recent literature, a robust set of out-of-sample statistics, including the Clark and West statistic, Diebold-Mariano statistics and Theil's U ratio are used to evaluate the forecast performance. Current results from the Theil's U ratio and CW statistics shows the Taylor rule incorporating the wealth effect improves the short run exchange rate forecast performance.

Finally, we model the exchange rate from 1975 to 2008 as a Smooth Transition Regression (STR) based model in which a series of economically meaningful transition variables drive the movement across exchange rate regimes. The overall findings show strong evidence supporting the nonlinear relationship between the exchange rate and economic variables. Moreover, the STR Taylor rule models of the exchange rate substantially outperform both the random walk model and the linear Taylor rule model in forecasting the exchange rate.

# Chapter 1 Introduction

The exchange rate, as with other macroeconomic variables such as nominal interest rates, is key determinant of a country's relative level of economic performance. It serves a variety of functions in the modern world, for instance, policymakers require an understanding of how exchange rates influence the macroeconomic environment in order to set monetary policy appropriately. On the basis of that understanding, central banks may wish to initiate policies in an attempt to affect and control their currency. Multinational and domestic companies are also concerned with currency movements, as any change in the exchange rate may substantially change their material costs and the price of their goods in the international market. Investors and fund managers investigate movements in the exchange rate, hoping to profit from its fluctuations or mitigate risk arising from exchange rate movements. With the continuous development of global capital markets and financial services, the economics of the exchange rate remains one of the most important areas in financial and international economic research.

Currencies, like other financial assets, fluctuate daily and are influenced by a variety of factors. The importance of each factor may differ both across countries and, for any given country, over time (Cheung et al., 2005). Therefore, it is difficult to identify which factor is the most important for the determination of the exchange rate. In addition, different countries may have differing degrees of sensitivity with which their currencies respond to various macroeconomic factors. Standard theoretical economic models suggest that exchange rates are influenced by macroeconomic fundamentals such as the money supply, interest rates, real output level, price level or inflation.[①] However, identifying empirical relationships between each of these

[①] These are fundamental economic factors which have been widely used in the literature to model exchange rates. A detailed discussion of these models can be found in the literature review.

with the exchange rate has not recently been an easy task. The high volatility and complex nature of exchange rates make them very difficult to model. Since the start of the floating exchange rate era, the puzzle as to how exchange rates are linked to macroeconomic fundamentals has been one of the central challenges confronting international economics.

One of the central issues in this field is the forecasting of the future exchange rate. Over the years, economics has suggested a number of theories as a basis for forecasting the exchange rate. For example, the widely known purchasing power parity theory (PPP) which links exchange rates to price levels, the flexible price monetary model (Frenkel,1976), the sticky-price monetary model (Dornbusch,1976) and the portfolio balance approach (Branson,1977). These models have dominated the literature on the exchange rate during the 1970s and 1980s. Moreover, more recent literature has pointed to a new direction in macroeconomics by incorporating endogenous Taylor's (1993) rules into exchange rate models. Unlike the above models, this more recent approach reflects how monetary policy is actually conducted or evaluated and offers a different explanation of exchange rate dynamics.[2]

Apart from those who have attempted to find connections between exchange rates and macroeconomic fundamentals, recent research has started to extend the studies of exchange rates by considering the effect of other variables into standard approaches to exchange rate determination, such as cross-country patterns or financial variables. For example, Chen (2002) incorporated commodity export prices into standard exchange rate models for three commodity-exporting countries (Australia, Canada, and New Zealand) during the period 1973-2001. Both in-sample and out-of-sample performance was examined using monetary and PPP models. They found world commodity prices helped to explain nominal exchange rate movements in these countries. Amano and Van Norden (1998) have studied the

[2] These models will be discussed further in Chapter 2.

important relationship between the real domestic price of oil and real effective exchange rates for Germany, Japan and US over the post-Bretton Wood period. A simple model is developed where the exchange rate is determined by exogenous changes in the terms of trade. Overall, they found that the real oil price captures exogenous terms-of-trade shocks which is an important factor in determining long-run real exchange rates.

Despite the variety of models, estimation methods, forecasting techniques used in the modelling and appraisal of exchange rates and their forecasting, many questions regarding currency movements remain unanswered. MacDonald (1999) classified various puzzles on the exchange rate into three main categories: the first area is concern with understanding the relationship between exchange rates and various fundamentals. The second area investigates whether out-of-sample forecasting performance can beat a random walk. The last one seeks to explain the high volatility and persistence of the real exchange rate. This study aims to develop Taylor rule based models and use some recently developed techniques in econometrics, to try and finding some answers to these puzzles.

Due to the breadth of research, a truly comprehensive review of all exchange rate models is not possible and certainly beyond the scope of this thesis. The following literature review in Chapter 2 begins with a brief discussion of both traditional and newly proposed exchange rate models, with a particular focus on the Taylor rule type exchange rate model.

This study focuses on three exchange rates (Sweden, Australia and UK vis-à-vis the US dollar) and using quarterly data spanning from 1970 to 2008. These countries have been selected because all of them have highly liquid financial markets, free floating exchange rates and similar monetary policy regimes.

This thesis makes an attempt to answer the first two above mentioned puzzles. Firstly, the effects that different financial variables have on exchange rate determination are investigated and I tests whether augmenting them with additional fundamentals can improve their explanatory power of the exchange rate models. Secondly, I evaluate whether this approach improves their ability to forecast exchange rates out-of-sample.

Based on the Taylor rule exchange rate model developed by Molodtsova and Papell (2009), I have incorporated both stock price and house price to represent the effects of wealth. Both in-sample goodness of fit and out-of-sample forecasting ability is examined using the standard single equation Taylor rule framework. Later in Chapter 6, the non-linear behavior of the model has also been analysed.

The main contributions to the literature related to this study include the incorporation of wealth effects into the Taylor rule exchange rate model, as has already been done in other exchange rate models. Unlike much of the previous literature in this area, I have assessed the time series properties of the data and incorporated dummy variables into the models to account for the structural breaks. Finally, to my knowledge, this is the first time that this type of non-linear estimation has been applied to these models and used for non-linear forecasting.

This thesis will be divided into eight Chapters. Chapter 2 presents a critical overview of the main asset-market approach in the exchange rate literature. This Chapter is divided into seven sections. The first three sections give a brief introduction to some of the main macroeconomic exchange rate models used since the start of the floating exchange rate era, including their forecasting ability and limitations. It discusses a variety of predictors, models, data and methodologies which have been used in the exchange rate determination literature to identify specific models which were used to predict the exchange rate. The aim of these sections are to identify the difficulties in estimating these models and the poor performance of asset-market models in forecasting exchange rates out-of-sample. The last four sections provide a summary of the developments in the Taylor rule models. Firstly, we show how the Taylor rule as a description of the central bank's behavior is derived. Then, using the Engel and

West (2006) framework, I briefly describe how exchange rate forecasting equations can be derived from the Taylor rule. In these sections, we address the advantage of Taylor type models over traditional asset-market models in studying exchange rates. The many favourable features of this type of model give us the motivation to build on this area of the literature. Moreover, we address several issues concerned with Taylor rule forecasting as mentioned in previous studies, some of which we have been attempting to answer to some extent in this study and some of which are still under exploration.

Chapter 3 discusses the exchange rate regimes and policies of the countries included in the study. Since the Taylor rule exchange rate model is derived from the Taylor rule – a reaction function used to evaluate the actions and policies of central banks. Therefore, changes in monetary policy, especially to the exchange rate policies, might influence the response of the exchange rate. Although the effect might be different to that expected, for example, there may be time delays to its effect on the wider economy. An understanding of exchange rate regimes and policy settings will help us to better understand the movement in exchange rates. Moreover, it provides useful information to assist with the explanation of different country's estimated transition functions over time in Chapter 6.

Chapter 4 investigates whether wealth effects help explain nominal exchange rate movements and assesses the in-sample performance of our Taylor rule exchange rate models in explaining exchange rate movements. The literature review stresses the close linkage between wealth effects and the exchange rate. In this chapter, we conduct in-sample tests of the models using OLS, and then augment the models with the stock price index or house price index. Our results show that wealth effects are a reliable determinant of exchange rate behavior with the in-sample fit of several models improving substantially when wealth effects are added.

Besides, a more detailed analysis of the properties of the Taylor rule exchange rate are undertaken. These involve a discussion and analysis of the predicted coefficient signs in the models, examining the time series properties of the variables and identifying any structural breaks in the Taylor type exchange rate models. Since the estimation period covers several exchange rate regimes, the Lee and Strazicich (2003) test is employed to detect the possibility of structural breaks. The presence of structural breaks also gives us motivation for the nonlinear analysis of the model. This will be discussed in more detail in the final empirical chapter.

Furthermore, this section considers not only the baseline case of the Taylor rule exchange rate with inflation and the output gaps as fundamentals, but also a variety of specifications of the various Taylor rule models examined. For example, whether the lagged interest rates are important in explaining exchange rate movements. Another area we have paid attention to is the output gap measure. The output gap can be considered as the difference between actual output and the potential output of the economy. Normally the output is measured using the industrial production index (e.g. Wilde, 2012; Molodtsova and Papell, 2009; Ince, 2014). This study uses GDP to measure output. Furthermore, the HP-filter is used to estimate the output gap.

Chapter 5 examines the performance of our Taylor rule models in terms of out-of-sample forecasting performance, in particular discussing their performance against the results of Molodtsova and Papell (2009) and the benchmark random walk specification. The forecast is based on our results from the Taylor rule estimation in Chapter 4. A key study is Molodtsova and Papell (2009) who derived a simple version of the Taylor rule model and demonstrated that it can outperform a variety of monetary models as well as the naive random walk with some specifications. Therefore, it is of great interest to discover whether such models incorporating wealth effects have superior predictability. A variety of specifications are examined with rolling forecasts in order to investigate whether or not these specifications can improve out-of-sample predictability using this class of exchange rate model.

One debate in the exchange rate forecasting literature is to decide on which type of goodness-of-fit measures should be used for comparing the out-of-sample forecasting performance. This has been discussed in chapter 2. Due to this debate, a number of goodness-of-fit measures (i.e. in addition to the CW statistic) are used for comparing the predictability of our Taylor rule models. Section 5.3 provides an introduction to these measures as well as discussing their variability in measuring the forecasts.

Since the estimation period is over 3 decades, we have also considered whether or not changes in exchange rate regimes have an impact on the Taylor rule exchange rate predictability. This will be done by investigating how the use of different forecasting window sizes affects the out-of-sample exchange rate predictability.

After chapter 5, we have discovered the importance of the Taylor rule as well as its limitations in studying the linear relationship between exchange rate movements and macroeconomic fundamentals. Models assuming an endogenous monetary policy provide some interesting results with regard to the exchange rate, especially regarding its short-term predictability. However, no single model can consistently provide a superior performance across all countries. Therefore, our interest in chapter 6 will focuses on how to improve the Taylor rule exchange rate models from a non-linear perspective.

Chapter 6 explores the possibility of nonlinearity in the relationship between exchange rates and Taylor rule fundamentals. This is largely motivated by the nonlinear approach presented in a number of studies with regard to either the Taylor rule or exchange rate models. This section starts with a review of some theoretical work covering the significance of nonlinearities in the Taylor rule and the UIRP relationship. Particular focus is on analysing the various economic theories explaining the possible nonlinearity and identifying their form. In order to account for the nonlinear features, we apply a family of STR models to evaluate the adequacy of the Taylor rule exchange rate model specifications. The reason for choosing this class of model is demonstrated in section 6.3.1. A variety of transition variables has been selected according to different theories. Then, following the modelling approach proposed by Granger and Teräsvirta (1993a) and Teräsvirta (1994), we investigate empirically the evidence of nonlinearities in the Taylor rule exchange rate parameters. The nature of the nonlinearity is also verified. For example, is the nonlinearity resulting from the presence of outliers? Moreover, a variety of diagnostic test are performed in order to assist the decision making on the best performing transition variable. Specific tests have also been performed to check whether models are subject to additional nonlinearity after the first type has been controlled for.

Further, through the use of a non-linear forecasting techniques, we evaluate the performance of nonlinear models in providing accurate forecasts. In order to comparing it with the forecasting performance from the linear model, this section uses the same goodness-of-fit measures as in chapter 4. Moreover, the study in this chapter has extended the nonlinear specification of the Taylor rule exchange rate model by considering the effect of stock prices or house prices in the linear estimation.

Chapter 7 concludes and outlines some suggestions for future research.

# Chapter 2 The Literature on exchange rate modelling

The collapse of the Bretton-Woods fixed exchange-rate system in the early 1970smarked the start of the modern research on exchange-rate determination. [③] Testing exchange rate models became popular after the major industrialized economies adopted floating exchange rates. Forecasting the exchange rate using models that were conditioned on economically meaningful variables has been at the top of the research agenda in international finance for a long time, and yet empirical success remains elusive. The following literature review aims to assess the main studies on the exchange rate after the fall of the Bretton-Wood system.

## 2.1 Conventional Asset-Market Exchange Rate Modelling

The period from the mid-1970s to the early 1980s has been characterized as "a 'heroic age' of exchange rate theory."[④] During that time, international economists focused their attention on three major structural approaches to modelling exchange rates. These are the flexible-price monetary models, sticky-price monetary models, and portfolio balance models. Although those models has been rejected by most researchers due to the result that none of the specifications could outperform the random walk model in predicting the exchange rate out-of-sample (Meese and Rogoff, 1983ab; MacDonald and Taylor, 1992; Taylor 1994). It is worthwhile studying the exchange rate models based on macroeconomic fundamentals, such as the money supply, trade balance and national income, as a basis for understanding

[③] The fixed exchange rate system established in 1944, this system determined that each country should fix its exchange rate in relation to the U.S. dollar, which was convertible to a fixed amount of gold.

[④] Krugman (1993b, p6)

the behaviour of the exchange rate. The sections below give a brief review of the major exchange rate models, including the theory behind each model and how efficient they are in modelling the exchange rate and provides a context for the model developed later on. The main theoretical assumption of the asset-market models is perfect capital mobility. Moreover, the models assume no transaction costs and capital controls.

### 2.1.1 Purchasing Power Parity

PPP is one of the simplest macro fundamental exchange rate models. The absolute purchasing power parity implies that the exchange rate between two countries should be equal to the ratio of two countries relevant price levels. A unit of currency of one country will have the same purchasing power as in a foreign country.

$$s_t = p_t - p_t^* \tag{2-1}$$

Relative PPP posits that changes in the exchange rate are equal to changes in relative national price levels.

$$\Delta s_t = (\Delta p_t - \Delta p_t^*) \tag{2-2}$$

Where $s_t$ denote the logarithm of the spot exchange rate, defined as the price of foreign currency in terms of the domestic. $p_t$ and $p_t^*$ are the logarithms of the domestic and foreign price levels, respectively.

In the early 1970s, when the monetary approach dominate the exchange rate determination literature, economists assumed PPP held continuously (e.g. Frenkel, 1976; Frenkel and Johnson, 1976; Taylor, 1994; Frankel and Rose, 1995). However, this strong proposition, together with the simple monetary approach to the exchange rate, was largely abandoned in the mid- to late 1970s. This is later defined by

Obstfeld and Rogoff (2001) as the 'Disconnect puzzle'.[5] MacDonald and Taylor (1992) argue that the early encouraging result was due to the relatively stable dollar and lack of a long enough data set to test the theory. In the 1980s, studies discovered that real exchange rates follow a random walk (Adler and Lehmann, 1983). This result reduced further the confidence in PPP. From then on, it becomes increasingly clear that continuous PPP could not hold. The nominal exchange rate is far more volatile than the relative price levels. More recently, in an extension of this literature, studies have tested for the existence of long-run PPP. They tested for the stationarity of real exchange rate and interpreted the null of stationarity as equivalent to the existence of long-run PPP (Flood and Taylor, 1996). The results are inconclusive. Some authors found evidence in support of the long-run PPP hypothesis for the period of floating exchange rates. For example, Cheung and Lai (1993) and Lothian and Taylor (1996) for the major industrialized economies, McNown and Wallace (1989) for the exchange rate of high-inflation countries. Others found little evidence of long-run PPP (e.g. Mark, 1990). A popular explanation for the failure of long-run PPP is that the data span is simply too short (i.e. only data of the post-Bretton Woods period). It fails to provide a reasonable degree of test power to reject the null hypothesis of no cointegration.

### 2.1.2 Uncovered Interest Rate Parity

The uncovered interest rate parity (UIRP) assumes perfect substitutability between domestic and foreign bonds. The asset holders are indifferent as to the composition of their bond portfolios as long as the expected rate of return on the two countries bonds is the same (Frankel 1983a).

If this is the case, then the expected foreign exchange gain from holding one currency rather than another - the expected exchange rate change, must be just offset by the

[5] An overview of the disconnect puzzle and other puzzles in international macroeconomics can be found in Obstfeld and Rogoff (2001).

opportunity cost of holding funds in this currency rather than the other – the interest rate differential. This condition is referred to as the UIRP.

$$\Delta s_{t+1}^{e} \equiv E_t s_{t+1} - s_t = i_t - i_t^{*} \tag{2-3}$$

where $\Delta s_t^e$ is the expected rate of appreciation of foreign currency. $i_t$ and $i_t^*$ are the nominal interest rates available on similar domestic and foreign securities respectively.

The theory of UIRP is a crucial concept to many international macro-econometric mode (Bjørnland, 2009). For example, the monetary exchange rate model and the Taylor rule exchange rate model. The empirical failure of UIRP is widely discussed in the literature and can be refer as the uncovered interest rate parity puzzle.

Despite the large amount of evidence against the UIRP (e.g. Bilson, 1981; Fama, 1984; Engel, 1996), some recent works found evidence supporting the theory. Bekaert, Wei and Xing (2007) found the statistical evidence of UIRP depends on the currency pair not on the horizon. Kearns and Manners (2006) argue that the UIRP are more likely to hold for relatively small economy. Aggarwal (2013) provide empirical support for Kearns and Manners' (2006) argument based on pound-US dollar and Pound-Australian dollar currency pair. Backus et al. (2013) restated the UIRP puzzle in terms of monetary policy and found that asymmetric Taylor rule which incorporate a real exchange rate resolve the UIRP puzzle.

### 2.1.3 Flexible Price Monetary Models

This model is attributed to Frenkel (1976), Mussa (1976) and Bilson (1978). The central assumption is that PPP continuously holds. Moreover, it assumes stable, log-linear money demand functions at home and abroad. The demand for money, $m$, is assumed to be linearly dependent on real income, $y$, the price level, $p$ and the level of the nominal interest rate, $i$ (all variables are in logarithmic form except interest rates).

$$\begin{gathered} m = p + \kappa y - \lambda i \\ m^* = p^* + \kappa y^* - \lambda i^* \end{gathered} \tag{2-4}$$

where $m$ and $m^*$ are the logs of the domestic and foreign money supplies, respectively.

Combining equation (2-4) with the UIRP condition (2-3) and the PPP condition (2-1), the forward looking flexible price monetary equation:

$$s_t = (m_t - m_t^*) - \kappa(y_t - y_t^*) + \lambda \Delta s_{t+1}^e \tag{2-5}$$

Equation (2-5) says that the exchange rate, as the relative price of moneys, is determined by the supply and demand for money. This is really just a purchasing power parity model of the exchange rate and assumes perfect price flexibility. An increase in the supply of domestic money causes a proportionate depreciation. An increase in the demand for domestic money causes an appreciation.

However, due to the high volatility of real exchange rates during the 1970s. One of the central assumptions of flexible-price monetary models, the continuous PPP, was abandoned by Dornbusch (1976). In fact, the exchange rate is more volatile than the price levels under a floating rate exchange rate system. This led to the development of the sticky-price monetary model which can be viewed as an extension of the flexible-price model.

### 2.1.4 The Sticky Price Monetary Model

Dornbusch (1976) took the assumption that prices are perfectly flexible in the short run, as unrealistic. Instead, PPP is assumed to hold only in the long run. Because the goods prices adjust slowly relative to asset prices, the spot rate can deviate from its long-run equilibrium value in the short run. This model allows short-term overshooting of the nominal and real exchange rate above their long-run equilibrium level.

Assume long run PPP:

$$\bar{s} = \bar{p} - \bar{p}^* \tag{2-6}$$

where a bar over a variable denotes long-run equilibrium.

In the short run, the prices not only adjust gradually over time in response to excess goods demand but also move in line with the underlying inflation rate, $\bar{\pi}$.[6]

$$\Delta s_t^e = -\theta(s - \bar{s}) + \bar{\pi} - \bar{\pi}^* \tag{2-7}$$

Combine (2-7) with the assumption of UIRP (2-3), we derive an expression for the gap between the current spot rate and its equilibrium level

$$s - \bar{s} = -\frac{1}{\theta}[(i - \bar{\pi}) - (i^* - \bar{\pi}^*)] \tag{2-8}$$

Therefore the sticky price monetary equation of exchange rate is:

[6] This is the Dornbusch model as extended to the case of secular inflation in Frankel (1979). The inflation rate $\bar{\pi}$ and $\bar{\pi}^*$can be thought of as the countries'' expected money growth rate.

$$s = (\bar{m} - \bar{m}^*) - \kappa(\bar{y} - \bar{y}^*) + \lambda(\bar{\pi} - \bar{\pi}^*) - \frac{1}{\theta}[(i - \bar{\pi}) - (i^* - \bar{\pi}^*)] \quad (2\text{-}9)$$ [7]

In the short run, the foreign exchange market will overact to a monetary changes and the exchange rate deviates from its equilibrium path to achieve a new short run equilibrium. Gradually, as goods prices eventually respond and shift to a new equilibrium, the exchange market continuously re-prices and approaches to its new long-term equilibrium level with the speed of adjustment $\theta$ over time.

Both the flexible and sticky price monetary models are classified as the monetary model. They assume perfect substitutability of domestic and foreign assets and were popular in the literature as models for exchange rates in the early 1970s. However, since the collapse of the fixed exchange rate in the late 1970s, both the flexible- and sticky- price monetary models had limited success in explaining the variations in exchange rate movements. For example, Frankel (1984) and Backus (1984) showed that the monetary models lose the ability of tracking the exchange rate in-sample once the sample period is extended beyond 1974. Recent papers have tested the monetary model of the exchange rate using cointegration techniques. For example, MacDonald and Taylor (1994) use the forward-looking monetary model and find evidence of cointegration between exchange rates and the fundamentals (both in logarithm form) for the US/Deutschmark exchange rate during the period 1976 to 1990. However, this is not stable, Sarantis (1994) found the cointegrated relation disappeared using a similar period for the pound-sterling exchange rates of US, Germany, Japan and France.

[7] Frankel (1984).

### 2.1.5 The Portfolio Balance Model

In the early 1980s, a number of researchers attempted to explain the behavior of exchange rates with portfolio-balance models. Examples include Kouri and Porter (1974), Branson (1977) and Girton and Henderson (1977).

The key distinguishing feature of the portfolio balance model is the assumption that the domestic and foreign assets cannot be regarded as perfect substitutes. Thus, unlike in the flexible-price and sticky-price monetary approaches, the UIRP condition does not prevail. Moreover, the portfolio balance models were generally based on ad hoc assumptions about exchange rate expectations and are not based on PPP. So the model allows for real exchange rate fluctuations which are restricted in the monetary model. Empirical tests of the portfolio balance models are provided, among others, by Obstfeld (1982), Frankel (1983b) and Lewis (1988). The results are mixed. Later, MacDonald (2007, p.198) concluded that "empirical studies on the portfolio balance approach are not particularly supportive of the model."

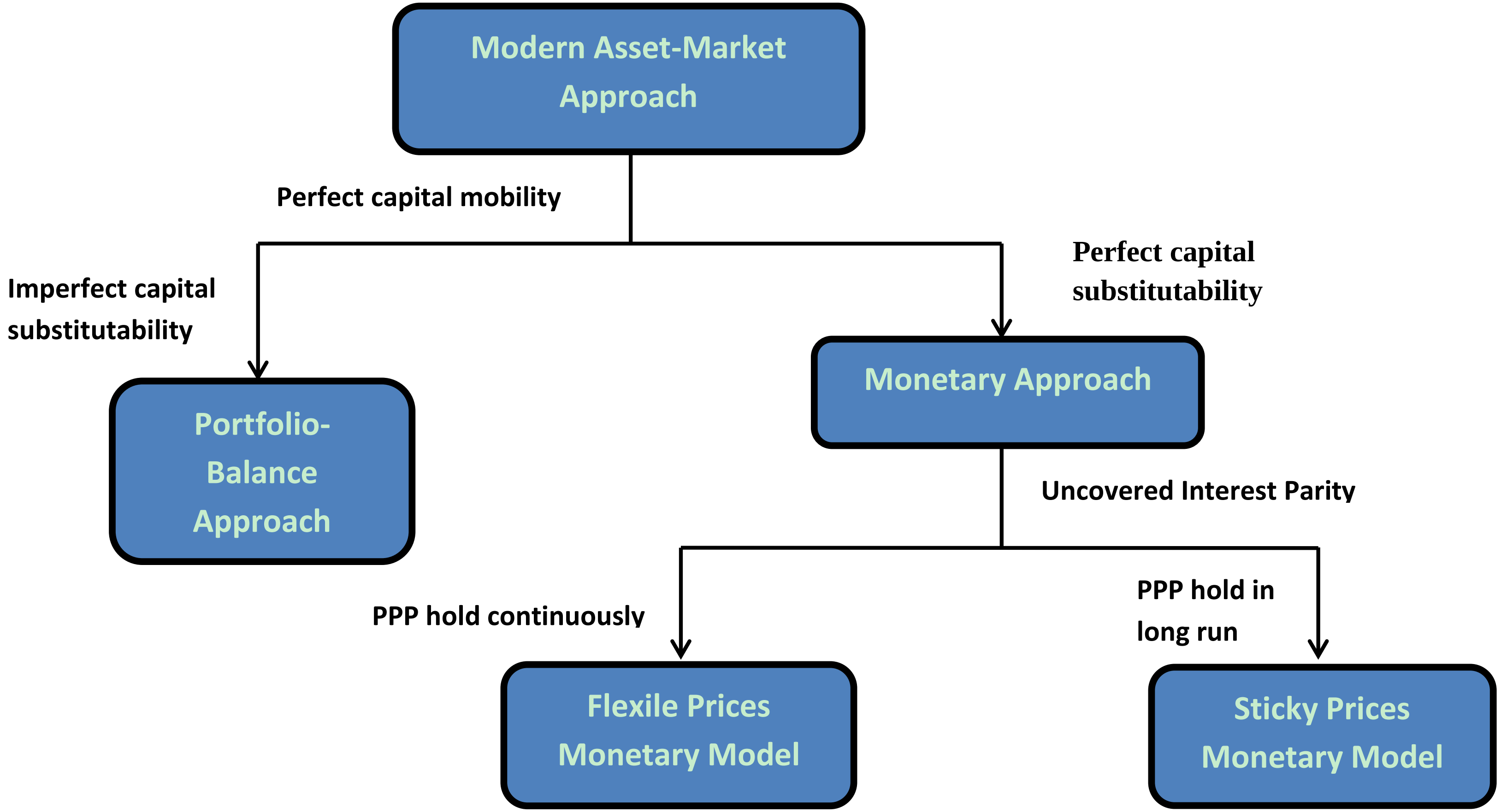
### 2.1.6 Meese and Rogoff (1983a and 1983b)

Beginning in the 1980s, Meese and Rogoff produced a landmark paper on the exchange rate. Their seminal work involves the use of various macro-based exchange rate models to forecast the exchange rate which were typically included in the exchange rate studies of the 1970s. The data used are monthly and the sample period is from 1973:03 to 1981:06. By testing the dollar/pound, dollar/mark, dollar /yen and trade-weighted dollar exchange rate at many time horizons, ranging from one to twelve months. They have compared the out-of-sample performance of those models with forecasts produced by a random walk.

The main conclusion of the Meese and Rogoff paper is that, comparing the root mean square errors (RMSEs), none of the structural exchange rate models were able to provide a better out-of-sample forecast than a simple random walk. Although there is some evidence of predictability for longer horizons such as beyond twelve months (e.g. Meese and Rogoff, 1983; Mark, 1995; Engel et al., 2007), these models are unstable in the sense that the minimum MSPE models have different coefficients at different time horizons (Meese and Rogoff, 1983b). Attempts to forecast at short horizons of one month to one year have been far less successful.

Following the results of Meese and Rogoff (1983a,1983b), the economics profession was forced to confront the fact that existing empirical models failed to significantly outperform a random walk model in predicting the behavior of the exchange rate, out of sample.

**Figure 2-1 Exchange Rate Models**



## 2.2 A Review of the Empirical Literature on Exchange Rate Forecasting (1980-2001)

Since the Meese and Rogoff (1983a, 1983b) study mentioned earlier, there have been a growing number of studies on exchange rate forecasting attempting to overturn the finding of Meese and Rogoff. Different forecasting methods, estimation procedures, test statistics and innovative structural models have been used in trying to solve the so-called Meese-Rogoff puzzle.

A few studies find the exchange rate predictability of monetary model can be improved by extend the forecast horizon. Mark (1995) used the mean correction error formulation of the monetary model to evaluate out-of-sample significance against a random walk. He took into account the nonlinearities in the data generation mechanism of the exchange rate. The study is based on a number of exchange rates including the US/Canadian dollar, US/Deutschmark and US/Swiss franc. Using quarterly data from 1973 to 1991, he found that exchange rate predictability generally improved once the forecasting horizons extended to one to four years.

Similar results were found by Chinn and Meese (1995), MacDonald and Taylor (1994) and Engel et al. (2007). Chinn and Meese (1995) use the statistical test of Diebold and Mariano (1995) to assess the significance of the forecast accuracy of Canada, Germany, Japan and the UK exchange rate relative to the U.S. dollar. Compared to the benchmark of the random walk, long-term predictability was presented for the German mark and Japanese yen exchange rate. MacDonald and Taylor (1994) use a multivariate cointegration technique to exam the monetary class of models for the Sterling-dollar exchange rate. Their results suggest long-run predictability with the monetary error correction model outperforming the random walk over all five forecasting horizons examined. The degree of improvement increased as the forecasting horizon was extended. Mark and Sul (2001) and Rapach and Wohar (2004) have employed panel data consisting of a set of similar countries. Using unit root and panel cointegration techniques, these studies found evidence of predictability in the old monetary models of the 1970s and 1980s, especially over longer horizons.

Soon after the discussion of improving exchange rate forecasting by extending the forecast horizon, there were subsequent works which have questioned whether predictability increases with the horizon. For example, Kilian (1999), Berkowitz and Giorgianni (2001) and Faust et al. (2003). They raised questions about the use of the bootstrapping techniques by Mark (1995) in evaluate out-of-sample exchange rate performance and show that the results of high and significant predictability in long horizons is due to a lack of cointegration between fundamentals and the exchange rate. Kilian (1999) reconciles Mark's (1995)'s bootstrap method by employing a less restrictive data generating process. However, his results give limited support for the monetary model and no evidence of increased long-horizon forecast ability. Berkowitz and Giorgianni (2001) focused on Mark's (1995) assumptions about the long-run behavior of the data series influencing the evidence of predictability. They showed that that if a one-period regression has a slope coefficient of zero, the coefficient of the long-horizon regressions, regardless the length of the horizon, will also be zero. They have also considered the case where the exchange rate and macroeconomic fundamentals were integrated and argued the distribution of the test statistics will depend on whether or not there is cointegration. The result of high and significant predictability over longer horizons in Mark (1995) can be explained by a lack of cointegration between the fundamentals and exchange rate. Faust et al. (2003) took into account data revisions and data accumulation through time in Mark's (1995) data by use most relevant data and found the long horizon predictability largely disappeared.

In summary, these authors have shown that the forecasting ability of the exchange rate is crucially dependent on the assumptions of the data generating process and long-horizon regressions of the monetary model does not improve upon short-horizon regressions.

Frankel and Rose (1995) describe evidence to date as indicating that "no model based on such standard fundamentals ... will ever succeed in explaining or predicting a high percentage of the variation in the exchange rate, at least at short- or medium-term frequencies." After more than two decades, the comprehensive study by Cheung, Chinn, and Pascual (2005) confirmed Meese and Rogoff's (1983a, 1983b) conclusion. They examined the out-of-sample performance of the models developed during the 1990s including: interest rate parity, monetary, productivity-based and behavioral exchange rate models, and applying new econometric techniques at different time horizon. Having the Mean Square Error as basis of comparison, the authors concluded that, in line with a great part of the existing literature, some models perform well for certain time horizon or specific exchange rates, but none of the models consistently outperform the random walk at any horizon. Sarno and Taylor (2003) claimed that 'The empirical results tended to be fragile in the sense that they were hard to replicate in different samples or countries.'

## 2.3 Solutions to the Exchange Rate Forecasting Puzzle

New developments in the mid-2000s changed the perspective and shed some new light in the field. Since then, a growing number of papers have been reporting results of more positive short-term forecasting. Researchers have developed new structural models, innovative estimation procedures and more powerful out-of-sample test statistics.

### 2.3.1 Panel data and Taylor rule

Using panel data from a set of similar countries is one line of research after the mid-2000s. These studies have mostly focused on the monetary models of the exchange rate. Influential papers include Mark and Sul (2001), Groen (2005) and Rapach and Wohar (2004).

Another line of research focuses on country-by-country estimation and assumes an endogenous monetary policy exists in the exchange rate based on Taylor rules. The review of the literature for these more innovative and realistic models is discussed in section 2.6 and 2.7.

Mark and Sul (2011) further investigate conditions under which forecasts of the exchange rate using pooled panel-data regressions are more accurate than those based on time-series regressions. They found using the mean square error that forecasts based on pooled panel data regressions tend to dominate forecasts based on time series regressions and the random walk model when the sample size is small and slope heterogeneity across individual countries not too large. In their empirical study, they tested out-of-sample forecasting power using monthly data from January 1999 to January 2010 for the US dollar exchange rates against more than 20 countries. By comparing the MSPE, they found that the pooled forecasts will dominate the time-series forecasts for Columbia, the Philippines, Taiwan, Russia, Singapore, Hungary, Denmark, and the Euro zone. Predictions for these exchange rates should be generated by the pooled panel data model. Currencies such as Sweden, the UK, Japan, and Israel should employ time-series regressions. However, their study has focused on the simple monetary and PPP models only.

### 2.3.2 Accounting for Nonlinearity

Various papers discuss the possible reason for the failure of the economic exchange rate models. The possibility of inadequate economic models for exchange rate forecasting has been discussed as one reason for the failure of economic models to beat the random walk forecast. Kilian and Taylor (2003) argue that the underlying economic theory of exchange rate models is fundamentally sound. However, there are various non-linearities in deviations of the spot exchange rate from economic fundamentals. The linear forecasting models of the exchange rate failed because they did not considered those important nonlinearities in the data.

Bleaney and Mize (1996) have investigated nonlinearities in exchange rates with a number of currencies (US dollar, Japanese yen, UK sterling Australia dollar and German Mark)  using quarterly data from 1973-1994. They introduce a cubic model which provided the simplest form of sign-preserving nonlinear relationship. The positive results for the cubic model provide evidence of nonlinearity in the exchange rate in the countries studied.

Taylor and Peel (2000) argued that nonlinearity between fundamental variables and the exchange rate might explain the previous results of only long-run predictability for the monetary model or simple PPP model. They tested this hypothesis using quarterly data for the dollar-sterling and dollar-mark exchange rates over the floating rate period. The results are in general in support of their hypothesis with significant evidence of nonlinearity found in the series describing deviations of nominal exchange rates from monetary fundamental equilibrium levels. Furthermore, they show this nonlinearity can be described by an exponential smoothing autoregressive model.

Kilian and Taylor (2003) questioned the linear vector error correction model framework for modelling exchange rates. Focusing on the PPP models, they provide empirical support for nonlinear dynamics in exchange rates for seven countries over the post-Bretton wood period. In conclusion, they argued that, with the appropriate nonlinear structure, economic models of the exchange rate predicted well at horizons of two to three years.

López-Suárez and Rodríguez-López (2011) have studied whether the non-linear behavior of the real exchange rate can help to explain the lack of predictability of nominal exchange rates using the PPP model. A smooth transition error correction model was developed to compare with the results from a linear specification of PPP fundamentals.[8] Using the same panel of countries and time periods as Mark and Sul (2001), they found strong evidence of nonlinear predictability of nominal exchange rates. Moreover, their result differs from the findings of Mark (1995) that show exchange rate predictability improves in the long run. In contrast, they found better predictability in the short run. One possible explanation might be the nonlinear models with panel data perform better in the short run and traditional linear models do better in the long run.

### 2.3.3 Other influential fundamentals

Recently, in addition to the traditional exchange rate models, there have been papers test the exchange rate predictability by incorporating additional fundamentals, e.g. some influential cross-country pattern or financial variables.

Chen (2002) incorporates commodity export prices into the standard exchange rate models for three OECD commodity-exporting countries—Australia, Canada and New Zealand. All those countries have a significant portion of their production and exports in primary commodity products. By re-exam the performance of standard monetary models both in-sample and out-of-sample, Chen (2002) found that including commodity prices improves the in-sample fit of the standard models. However, in terms of forecasting, there appear to be no single model that consistently produces a superior prediction.

Guo and Savickas (2006) make use of variables which are commonly used for predicting the future behavior of monetary fundamentals, for example, the term structure of interest rates, credit risk, and the idiosyncratic risk of the United States'

[8] The model is based on the model used by Kilian and Taylor (2003) and is in the spirit of the generalized cointegrated system of Granger and Swanson (1996).

stock market.[9] Their analysis suggested that risk factors are important variables in predicting the exchange rate.

Amano and Van Norden (1998) study the relationship between oil prices and real exchange rate over the post-Bretton Wood period for the real effective exchange rates of Germany, Japan and the US. They find that oil prices have a strong impact on the US/Canadian dollar real exchange rate over the long-run horizon of twelve to twenty four months.

Before this study, Sarantis (2006) analysed exchange rate predictability using financial information from money, bond returns, equity returns and the derivative markets. He proposed using a Bayesian vector autoregressive model with time-varying parameters (BVAR-TVP) and applied it to the daily exchange rates of four large industrial countries (the U.S., UK, Japan and Germany). The results indicated by the MSPEs produced evidence that the BVAR-TVP forecasts strongly outperformed the random walk forecasts for all countries studied, suggesting the use of equity returns could produce good forecasts of the exchange rate.

To sum up, all the above studies found a strong link between exchange rate predictability and economic fundamentals. However, they have only focused on the traditional monetary models of the exchange rate. Motivated by these, I am going to study the exchange rate predictability with a wealth effect as an additional fundamental. Instead of using the traditional monetary model, I will employ the more empirically relevant Taylor rule model in studying the predictability of the exchange rate. A detailed review of the papers using the Taylor rule in exchange rate modelling is provided in the next section.

[9] Idiosyncratic risk are risk specific to one asset or asset group and can be eliminated by diversification.

## 2.4 The Taylor Rule in Exchange Rate Modelling

A new strand of literature has recently been developed, which identifies one of the major shortcomings of traditional exchange rate models as paying too little attention to the market's expectations of future values of the macroeconomic fundamentals (Bacchetta and van Wincoop, 2006; Engel and West, 2005). Most empirical monetary models of the 1970s and 1980s have been formulated in such a way that monetary policy has been considered exogenously. For example, in the monetary models of the exchange rate, the money supply has been used as the main variable to capture the monetary policy with respect to the fundamentals. They have not however tried to relate movements of the money supply to the macroeconomic variables that policy makers might target.

Modern monetary macroeconomic models have taken into account the expectation effect of the exchange rate and formulated the determination of interest rates and monetary policy quite differently. As discussed in Engel, et al. (2007)'s paper: Firstly, they emphasized on the endogeneity of monetary policy. Endogenous monetary policy means that monetary policy responds to changes in macroeconomic fundamentals and has important implications for the expectation of future fundamentals. Secondly, central banks have used short-term interest rates instead of the money supply as their policy instrument since the mid-1980s.

If central banks were using the money supply or monetary aggregates as instruments or target variables, then the old monetary models which model monetary policy exogenously in exchange rate determination would be a reasonable approach to exchange rate determination. However, if exchange rates are driven by expectations, then correctly modelling monetary policy is critical (Engel et al., 2007). For example, changes in current economic fundamentals may have a greater impact on exchange rates indirectly through the induced changes in expectations of monetary policy than through any direct channel such as the money supply.

Exchange rate models with the Taylor rule fundamentals have taken into account these two facts. The Taylor rule specified that central banks set nominal interest rates according to a Taylor rule type reaction function. The interest rate reaction function then interacts with other fundamentals to model exchange rate behavior. Different studies find that variants of the Taylor rule perform reasonably well in a variety of different models. For example, Svensson (1997), Ball (1997) and others suggest that Taylor-type rules in which the central bank reacts to current inflation and the output gap is approximately optimal for a closed economy in many circumstances. Engel and West (2006), Mark (2009), Clarida and Waldman (2008) and Molodtsova and Papell (2009) have explored the empirical performance of exchange rate models based on a Taylor rules for monetary policy. In general, their found this new type of model perform better than the random walk.

There is a disconnect between most research on exchange rate predictability, which is based on empirical exchange rate models of the 1970s, and the literature on monetary policy based evaluation, which is based on some variant of the Taylor (1993) rule. Recently, the use of Taylor rules to model exchange rate determination has become popular.

## 2.5 The Taylor rule model

### 2.5.1 The original Taylor Rule

Taylor (1993) postulated a simple monetary policy rule to be followed by central banks. In his original formulation, the rule posits that the Fed sets the real interest rate based on the equilibrium real interest rate, the inflation gap – the difference between inflation and the target inflation rate, and the output gap – the difference between GDP and potential GDP. In general, a Taylor rule looks as follows:

$$r_t = r^* + \alpha(\pi_t - \pi^*) + \beta y_t \tag{2-10}$$

where $r_t$ is the real interest rate, $r^*$ is the equilibrium level of the real interest rate, $\pi_t$ is the inflation rate, $\pi^*$ is the target level of inflation, $y_t$ is the output gap, or percent deviation of actual real GDP from an estimation of its potential level.

According to the Taylor rule, the real interest rate should be increased when inflation and output are above their targets, to bring these variables back to equilibrium. Combining this with the Fisher equation:

$$i = r + \pi \tag{2-11}$$

The Taylor rule can be specified in nominal terms:

$$i_t = r^* + \pi^* + \pi_t + \alpha(\pi_t - \pi^*) + \beta y_t \tag{2-12}$$

When $\gamma = 1 + \alpha$, the equation becomes:

$$i_t = i_t^* + \gamma(\pi_t - \pi^*) + \beta(y_t - y_t^*) \tag{2-13}$$

where $i_t$ represents the nominal interest rate and $i_t^*$ is the equilibrium nominal interest rate.

Taylor set the baseline nominal interest rate to equal the sum of the equilibrium interest rate, $r^*$, and inflation, $\pi^*$. The two remaining factors address the way that the policy should respond in the short-run to changing circumstances, i.e. output and inflation. The central bank raises the target for the short-term nominal interest rate if inflation rises above its desired level and/or output is above potential output. Taylor measures inflation as the change of the output deflator over the previous four quarters and measures the output gap as the percent deviation of real GDP from its trend.[10]

[10] Output deflator is measured as the ratio of nominal GDP to the real measure of GDP.

His own research on policy rules reported in Taylor (1993) is generally consistent with the above policy reaction function. Taylor uses a multi-country rational expectations model, simulating economic performance of the G-7 counties under several different monetary rules. He then examines the economic performance under different policy rules. The results show that policy rules that focus on exchange rates or policies that focus on the money supply do not deliver as good a performance as policies that focus on the price level and real output in describing current interest rate setting behavior. This is also proposed by Henderson and McKibbin (1993) and others.

### 2.5.2 Adjust Taylor rule for Open Economy

After the proposed Taylor (1993) rule, a number of paper start to test it on different sample period, for example, Taylor (1999) and Orphanides (2003). However, most of these analyses on monetary policy focused on closed economy models, where the short term interest rate linearly responds to changes in inflation and output only.

Open economy differ from closed economy. In open economy, behaviour of exchange rate are important in the sense that it transmit the effects of external shocks (Clarida et al, 1998; Ball, 1999). Furthermore, consumer price inflation is better than change of the output deflator in measure of inflation. In practice, central banks implementing inflation targeting have chosen to measure inflation based on difference on consumer prices (Leith and Wren-Lewis, 2009).

In order to derive optimal monetary policy rule for small open economy, Clarida et al. (1998) have made adjustment to the policy reaction function derived by Taylor (1993) by allow the central bank to respond to other variables, the real exchange rate. The baseline specification assumes there exists some degree of autonomy over domestic monetary policy. However, there may be important factors other than inflation and output that influence interest rate setting. For example, some central banks do not sacrifice monetary control completely, they may pursue policies to maintain the exchange rate within some reasonable bounds. In this case, the exchange rate will influence policy in addition to inflation and output.

By accounting for this feature into the Taylor rule interest rate reaction function, we have:

$$i_t = i_t^* + \gamma(\pi_t - \pi^*) + \beta y_t + \delta q_t \qquad (2\text{-}14)$$

where $q_t$ is the real exchange rate.

Clarida et al. (1998) provide evidence for some countries that supports this type of monetary policy rule. They used two sets of countries: the G3 (Germany, Japan, and the US) and the E3 (UK, France, and Italy) from 1974 to 1993. They estimated monetary policy reaction functions and found that the baseline specification of the reaction function does quite a good job of characterizing monetary policy for G3 countries post 1979.

The inclusion of the real exchange rate in an interest rate rule has also been considered by other researchers. Ball (1999) includes the real exchange rate in the exchange rate model to account for the fact that countries tend to raise interest rates in response to a real depreciation. Furthermore, he suggest that for open economy, an exchange rate should be included in the original Taylor rule. Moura and Carvalho (2010) estimated Taylor rules for seven Latin American emerging economies and found that Taylor rules that include exchange rates as explanatory variables yield superior predictability results.

### 2.5.3 The Taylor rule with a smoothing factor

The original Taylor rule predicts a much more variable interest rate path than what is observed in practice. When estimating the residual from the original rule proposed by Taylor, the result exhibits considerable persistence. The persistence in the policy rate is widely interpreted as evidence of interest rate smoothing. It seems that monetary policy makers do not tolerate the variability in interest rates prescribed by the Taylor rule. Central banks tend to smooth the changes in the interest rate.

In order to account for this, Clarida et al. (1998) specify a Taylor rule to include a smoothing factor in the form of the interest rate. The purpose is to posit that the interest rate only partially adjusts to its target within the period. This is done by including a lagged interest rate differential in the form of a partial adjustment model:

$$i_t = (1-\rho)\bar{\imath}_t + \rho i_{t-1} \qquad (2\text{-}15)$$

where $\bar{\imath}_t$ is the target rate implied by the Taylor rule, $i_t$ is the observed federal funds rate, and $\rho$ is the smoothing parameter.

$$i_t = (1-\rho)[i_t^* + \gamma(\pi_t - \pi^*) + \ \beta y_t] + \rho i_{t-1} + v_t \qquad (2\text{-}16)$$

where the parameter$\rho \in [0,1]$ captures the degree of interest rate smoothing. In this equation the interest rate is a weighted average of the previous period interest rate and some desired value that depends on the state of the economy.

Therefore, the coefficient $\rho$ in the above equation measures the degree to which the Fed does not follow the Taylor rule; the coefficient $(1-\rho)$ measures the speed of adjusting the actual federal funds rate towards the target rate implied by the Taylor rule. The further ρ lies above zero, the less closely the Fed would follow the Taylor rule. For example, if the Fed strictly followed the Taylor rule, then $\rho$ would be equal to zero.

Romer (2011) showed that there are several reasons for central banks to smooth their interest rates. Firstly, smooth interest rates will have a longer and larger impact on the economy which agents will realize. For example, a smooth increase in the interest rate will signal to market participants an expected higher interest rate in the future. Moreover, smooth changes in interest rates will reduce their volatility. Government usually dislike of financial market volatility and reversals. An immediate and sharp increase in interest rate might have a larger and negative effect on output and such effect might be quickly reserved. This will impair confidence in economy which policy makers always trying to avoid.

### 2.5.4 The Taylor rule and Real Time Critique

Recently, study on Taylor rule start to focus on the unrealistic assumptions on the data (e.g. McCallum, 1993; Orphanides, 2001; Orphanides and Norden, 2002). These studies argued that it is unrealistic to assume that monetary authorities' will respond to the current realized value for nominal and real level GDP or current price level. Use of these fully revised data will provide misleading result about past behavior of monetary policy.

Study of Orphanides (2001) highlight the importance of using real time dataset, which are available to monetary authorities at the time they formulate policy, in monetary policy related studies. A real-time dataset collects vintages of data that were actually available to researchers at each point in time (i.e. before data revisions applied to data). This is especially the case for output gap measures. Since real output data are revised routinely, so does the output gap estimates which using both actual and potential output. Nelson and Nikolov (2003) study different output gap measurement in case of UK and found that use fully revised data lead to incorrect estimates of authorities' behavior.

Orphanides and Norden (2002) looked at the problems of imprecise output gap estimates for the implementation of Taylor rule. Policy reaction functions estimated with final revised data might provide misleading result of how policy makers react to the information available to them in real time. Moreover, they shown that Taylor rule estimate based on quasi-real time output measure, where current vintage data is used, but the trend at period t is calculated using observations 1 to t, provide a more accurate description of policy than a Taylor rule based on revised data.

## 2.6 Taylor Rule Based Exchange Rate Modelling

To construct a Taylor rule based exchange rate determination model involves two steps: First, specifying Taylor rules for the home and foreign countries and subtracting one Taylor rule equation from the other. By doing so, we can obtain a formula for interest rate differentials as a function of economic fundamentals for inflation and the output gap, lagged interest rates and possibly real exchange rates if one or both central banks also target the purchasing power parity (PPP) level of the exchange rate. As a second step, we use the UIRP relationship to link exchange rate changes to interest rate differentials and, consequently, to economic fundamentals from the Taylor rules. These steps leave us with an expectational difference equation for the exchange rate that depends on contemporaneous economic fundamentals.

The literature on exchange rate models with Taylor rule fundamentals is relatively new. The recent works include Engel and West (2005), Engel and West (2006), Clarida and Waldman (2008), Mark (2009), Molodtsova and Papell (2009). Engel, Mark and West (2007) gave a brief review of some of these studies. The following is a present value model of the real exchange rate determination under Taylor rule fundamentals from Engel and West (2006) and Engel, Mark and West (EMW) (2007).

Engel and West (2006) and EMW specify the monetary policy rules for the home and foreign country as interest rate reaction functions for the central banks. Specifically, they assume the home country sets the nominal interest rate to target the deviation of expected inflation from the central bank's target, the output gap and possibly, the deviation of the nominal exchange rate from its purchasing power parity (PPP) value – that is, the real exchange rate, and the lagged interest rate. We summarize the monetary policy rule in the following equation.

$$i_t = \gamma_q q_t + \gamma_\pi E_t \pi_{t+1} + \gamma_y y_t + \delta i_{t-1} + u_{mt} \tag{2-17}$$

where $i_t$ is the interest rate, $E_t \pi_{t+1}$ is the expected inflation rate, $y_t$ is the output gap and $q_t$ the real exchange rate. $u_{mt}$ is shock to monetary policy rules. For the parameters, it is assumed $\gamma_q > 0$ , $\gamma_\pi > 1$ , $\gamma_y > 0$ , and $0 \leq \delta < 1$ .

The interest rate rule presented here has two deviations from the original Taylor Rule (1993). First, it has a forward looking characteristic. Second, it includes the real exchange rate. The real exchange rate is included to capture the notion that the monetary authorities in some countries tend to raise interest rates when their currency depreciates. For example, Clarida, Gali and Gertler (1998) find empirical support for this notion in Japan and some other countries.

The foreign country follows a similar policy rule:

$$i_t^* = \gamma_\pi E_t \pi_{t+1}^* + \gamma_y y_t^* + \delta i_{t-1}^* + u_{mt}^* \tag{2-18}$$

Notice that the benchmark country does not react to the real exchange rate.

The basic model assumes that the national and foreign central banks apply equal reaction parameters. Engel and West (2006) have made this assumption for convenience first, although later on they have used distinct parameters for the empirical analysis.

The international interest rate differential is simply derived by subtracting the foreign from the home monetary policy rule.

$$i_t - i_t^* = \gamma_q q_t + \gamma_\pi E_t \hat{\pi}_{t+1} + \gamma_y \hat{y}_t + \delta \hat{\imath}_{t-1} + \hat{u}_{mt} \tag{2-19}$$

where $\hat{x}$ represents country differences in inflation, output gap and interest rate.

The exchange rate is related to the interest differential via UIRP. Recall the UIRP:

$$i_t - i_t^* = E_t s_{t+1} - s_t \tag{2-20}$$

Upon subtracting the expected value of next period's inflation $E_t \pi_{t+1}$ from both sides of (19) and using the definition of $q_t$:

$$q_t = s_t - (p_t - p_t^*) \tag{2-21}$$

We obtain

$$(i_t - i_t^*) - E_t \pi_{t+1} = E_t q_{t+1} - q_t \tag{2-22}$$

Using (22) to substitute out for $(i_t - i_t^*)$ on the left hand side of (19), we obtain:

$$q_t = bE_t q_{t+1} + bE_t(1 - \gamma_\pi)\hat{\pi}_{t+1} - b\gamma_y \hat{y}_t - b\delta \hat{\imath}_{t-1} - b\hat{u}_{mt} \tag{2-23}$$

where $b = 1/(1 + \gamma_q)$, $0 < b < 1$

Later, Molodtsova and Papell (2009) derived another version of the exchange rate model based on the Taylor rule using similar techniques.

## 2.7 Review of the Empirical Literature on Taylor rule based Exchange Rate Forecasting Studies

The following section is a general review of the exchange rate literature relating to the Taylor rule model starting with a detailed description of some influential papers. These include Engel and West (2006), Mark (2009) and Molodtsova and Papell (2009). In general, the emerging evidence on the empirical performance of the Taylor rule models of the open economy are quite encouraging.

Engel and West (2006) and Mark (2009) use the Deutschmark-dollar exchange rates to test the importance of the Taylor rule fundamentals. They have constructed a fitted exchange rate for the Deutschmark-Dollar real exchange rate based on the behavioral equation. This fitted exchange rate is determined by Taylor rule fundamentals only. Both studies have used a present value Taylor rule model. The present-value model requires a measure of expected inflation, the output gap, and interest rates for all periods into the future. It also requires an estimate of future expected values of $\hat{u}_{mt}$. Engel and West (2006) and Mark (2009) treat the error term in similar ways - as unobservable in terms of the real exchange rate's determinants.

Engel and West (2006) do not include the lagged interest rate in the real exchange rate estimation. In their empirical work, they do not estimate Taylor rule parameters. Instead, they use parameter estimates from Clarida, Gali and Gertler (1998) who estimate $\gamma_q$=0.1 for Japan and Germany and hence a discount factor, b, is calculated. The constructed real exchange rate is then compared to that of the actual real exchange rate. They estimate the exchange rate model using monthly data from 1979:10 to 1998:12. In terms of the results, they find a positive correlation between the actual real exchange rate and the model based real exchange rates.

Mark (2009) investigates the link between the exchange rate and Taylor rule fundamentals in a similar way. However, there exists some differences. Firstly, he assumes market participants do not know the numerical values of the model's coefficients but use least squares learning rules to acquire that information. Secondly, he estimated Taylor rule parameters for two separate periods: 1976-1998 and 1999-2007 using quarterly data. Thirdly, he does not include the real exchange rate into the interest rate rule. In contrast to Engel and West (2006), he includes the lagged interest rate. The results of Mark (2009) provide evidence of a linkage between the real Deutschmark -dollar exchange rate and Taylor rule fundamentals. And their results are close to replicating Engel and West (2006).

Molodtsova and Papell (2009) evaluate the out-of-sample exchange rate predictability of models with Taylor rule fundamentals. They test 12 OECD countries vis-à-vis the United States for the post-Bretton Woods period starting in March 1973 and ending in December 1998 for the European Monetary Union countries and June 2006 for the others.

Based on different assumptions about the coefficients, they have derived sixteen nested Taylor rule exchange rate equations. The specification that produced the most evidence of exchange rate predictability was a symmetric model with heterogeneous coefficients, smoothing, and a constant.

The out-of-sample predictability of the Taylor rule's model is also compared with a random walk without drift as well as other conventional exchange rate models such as interest rate differentials, purchasing power parity, and three variants of monetary fundamentals. The results show that, the predictability power of the models is stronger with the Taylor rule fundamentals than with the other models for the same currencies and time periods especially at short horizons. At the one-month horizon, they find statistically significant evidence of exchange rate predictability at the 5% level for 11 of the 12 currencies. However, they do not find any statistical evidence that exchange rate predictability increases with the horizon. Beyond six months, they argue, exchange rate predictability with economic models is quite poor.

In their empirical work, the CW statistic is used to evaluate the out-of-sample performance of the exchange rate models instead of the commonly used Diebold and Mariano (1995) and West (1996) tests.

Since the seminal work of Meese and Rogoff (1983), it has been commonly accepted in the literature that in order to evaluate the out-of-sample performance of an exchange rate forecasting model, we test its predictive ability against a random walk. The most commonly used measure of predictive ability is the Mean Squared Prediction Error (MSPE). In order to evaluate out-of-sample performance of the models, Diebold and Mariano (1995) and West (1996) offer a commonly used procedure based on the MSPE comparison. However this method has not been used in Molodtsova and Papell (2009)'s study. They point out that these methods are not applicable in their study because two nested models are being compared, i.e. the random walk under the null is nested within the model under the alternative. According to Molodtsova and Papell (2009), the Diebold and Mariano (1995) and West (1996) tests lead to non-normal test statistics when applied to nested models. Instead of these tests, the authors favour the procedure proposed by Clark and West (2006, 2007) to test for predictive ability because the procedure was specifically developed for testing nested models.

The above mentioned studies have all found strong Taylor rules exchange rate predictability based on two specifications: at a short horizon and with a single time series equation. There are a few other studies using a panel data method with the Taylor rule models. Papers using panel data include Engel, Mark and West (2007), Engel, Mark and West (2015), Mark and Sul (2011), Galimberti and Moura (2013).

Engel, Mark, and West (2007) exam the predictive ability of the monetary model, Purchasing Power Parity (PPP), and Taylor rule fundamentals models in a panel regression framework. They use the CW statistic and find the panel estimates improve the forecasts relative to the single-equation estimation for the monetary and PPP models. The evidence is stronger with 16-quarter-ahead data than one-quarter-ahead forecasts. However, the Taylor rule fundamentals in the panel regression do not outperform the Taylor rule estimation in a single equation in forecasting the exchange rate. They attribute this result to the strong restrictions imposed by the panel. One of the restrictions of the panel is that the model is identical across all countries. However, the monetary rules differ too much across countries in practise.

They have constructed a fundamentals based Taylor rule exchange rate model with several specifications. Firstly, they have considered survey measures of expectations rather than measuring expected inflation and the output gap for all periods into the future. The surveys they use are from April 1997 to October 2006 for a number of countries including U.S., Japan, Germany, France, the U.K., Canada, Italy, the Netherlands, Norway, Spain, Sweden, and Switzerland. They do not allow for interest rate smoothing by including a lagged interest rate in the policy rule. The discount factor is based on Clarida, Gali, and Gertler (1998)'s estimation of $\gamma_q$ for the monetary policy rule in Germany. Moreover, they estimate the model as a panel by OLS and have ignored the possibility of correlation between the error term and the explanatory variables in the regression which could lead to inconsistent estimates of the coefficients.

The Taylor rule model they used is based on the Taylor rule in Molodtsova and Papell (2009), with out-of-sample forecasts replicating Mark and Sul (2001) with a longer sample. However, their results are different. Molodtsova and Papell (2009) find that the Taylor rule model is able to forecast well at short-horizons using univariate methods, while finding little support for the monetary or PPP models at any horizon. Engel, Mark, and West (2007) find out-of-sample forecasting power can be increased by focusing on panel estimation and long-horizons for the monetary and PPP models, but not for Taylor rule models.

Engel, Mark and West (2015) introduced factor models into the panel specification based on Engel, Mark and West (2007). They applied the technique to a panel of bilateral U.S. dollar rates against 17 OECD countries and compare the predictability of the models to a random walk model. They did not find strong predictability of exchange rates in the short run using the Taylor rule model. Although long-run exchange rate predictability is found using PPP models.

Galimberti and Moura (2013) study the relationship between exchange rate determination and monetary policy as represented by Taylor rules using panel data. They focus on a group of fifteen emerging economies that adopted free-floating exchange rates and inflation targeting and selected monthly data from January 1995 to March 2011. Evaluating out-of-sample performances based on various specifications of the Taylor rule. They found that models with exchange rates driven by forward-looking macro variables have a higher forecasting ability.

Groen and Matsumoto (2004) calibrate a dynamic general equilibrium model for the UK economy where monetary policy operates through interest rate reaction functions. Groen and Matsumoto (2004) and Gali (2009) - embed Taylor rules in an open economy dynamic stochastic general equilibrium model and trace out the effects of monetary policy shocks on real and nominal exchange rates, respectively. Clarida and Waldman (2008) studied the relationship between the Taylor rule, exchange rate and inflation. They show the covariance between an inflation surprise and nominal exchange rate can suggest something about how monetary policy is conducted. They argue that if central banks follow a Taylor type or interest rate rule, then a positive inflation surprise as represented by the Taylor rule slope coefficient on the expected inflation gap will cause exchange rates to appreciate for inflation targeting countries. This is because, given the central bank's conduct of monetary policy, the market would expect the central bank to raises interest rates to bring inflation back to target. This will lead to an appreciation, at least to begin with. This theoretical hypothesis has been proven based on ten countries for the period July 2001, to March 2005, of which eight are inflation targeting countries and two are not. Furthermore, they also find significant differences when comparing the inflation targeting countries and non-inflation targeting countries. For the non inflation targeting countries, there is no significant impact of inflation announcements on the nominal exchange rate.

Among all those Taylor rule-based exchange rate studies, there are mainly two types of estimation specifications. One is by the panel error correction method. Examples of this kind include Moura (2010), Moura et al. (2008). The other is the use of a country-by-country framework, for example, Molodtsova and Papell (2009) and Gloria (2010). According to Cheung (2005), these two specifications entail different implications for interactions between exchange rates and their determinants. The panel error correction specification is capable of capturing long-run interaction effects between exchange rates and economic determinants. Therefore, it is more efficient in forecasting long-run predictability of exchange rate and requires the model has a co-integrating relationship. This superior long-run out-of-sample predictability of error correction formulations has already been found in the literature, e.g. Mark and Sul (2001) and Rapach and Wohar (2004). Both have found exchange rate predictability over the long-horizon. Whereas the first difference model focuses more on the effects of changes in macro-economic fundamentals on the exchange rate. Cheung (2005) claims that the nature of the first-difference specification ensures that it uses ex-post values of variables in predicting the exchange rate, therefore it provides an informational advantage in forecasting. Galimberti and Moura (2013) combine these two specifications together in the study of emerging countries' exchange rate predictability. They further investigate the robustness of these two specifications and found little evidence in favour of the country-by-country time series approach.

Despite a large number of studies claiming to have found evidence of exchange rate predictability, some have argued that those encouraging results in out-of-sample forecasting is coming from misinterpretation of exchange rate forecasting methods. As argued by McCracken (2007), the traditional preferred minimum MSPE out-of-sample test statistics introduced by Diebold and Mariano (1995) and West (1996) are subject to undersize bias. Later, Clark and West (2007) introduced a new test statistic which is particularly suitable for nested exchange rate models. It soon became one of the most popular out-of-sample test statistics for studying exchange rates. Studies using the asymptotic CW as a test statistic include: Engel, Mark and West (2007), Gourinchas and Rey (2007), Molodtsova et al. (2008), Molodtsova and Papell (2009), Molodtsova et al. (2011), Rapach et al. (2008), Giacomini and Rossi (2010).

Rogoff and Stavrakeva (2008) suggest that the common structural models are not very good at forecasting exchange rates at short horizons. Recent evidence of success in short-run exchange rate predictability mainly come from misinterpretation of some new out-of-sample tests for nested models, over-reliance on asymptotic test statistics and a failure to check the robustness relative to alternative time windows.

They suggested that, in order to improve the reliability of the result, researchers should at least use test statistics other than the CW to test the robustness of their result.

A recent study by Ince (2014) have responded to some of the criticisms of Rogoff and Stavrakeva (2008). They have constructed a quarterly real-time dataset to study the US dollar exchange rate of nine OECD countries. Both panel error correction models and country-by-country frameworks have been used to study the predictability of purchasing power parity (PPP) and Taylor models. The results suggest that panel forecasts perform better over longer horizons (i.e., sixteen quarters ahead). Similar results have also been produced by Engel, Mark and West (2007). [11] In addition to this, they also found that Taylor models perform better over a shorter time horizon (i.e., one quarter), and panel estimation do not improve the performance of these models.

There are also papers incorporating additional fundamentals into the Taylor rule model for exchange rate forecasting. Gloria (2010) have tested the impact of commodities on exchange rate predictability. He used the same estimation and forecasting method as in Molodtsova and Papell (2009). The author selected Canada, Australia, New Zealand and South Africa in which the natural resources account for a considerable amount of their export revenue. The motivation is to improve the Taylor rule model given by Molodtsova and Papell (2009) by incorporating commodity prices into the econometric model. Evidence of the models with commodity prices outperforming both the random walk and models without commodity prices is found for Canada and South Africa.

Apart from Molodtsova and Papell (2009), Molodtsova and Papell have published a series of papers on Taylor rule based exchange rate forecasting. Molodtsova and

[11] Engel, Mark and West (2007) have used ex-post revised data, whereas Ince (2014) use real-time data.

Papell (2012) study the out-of-sample exchange rate predictability around the time of the financial crisis (i.e. 2007-2012). The Taylor rule model is based on a single equation version of Molodtsova and Papell (2009) and Engel et al. (2007) with additional credit spreads or financial condition indexes as indicators of financial stress. Results show that the Taylor rule model is superior to the other models in predicting the exchange rate. Molodtsova et al. (2008) have employed real-time data to evaluate out-of-sample predictability of the Dollar/Mark exchange rate. Real-time data are available to monetary authorities at the time they formulate policy. Strong evidence of predictability is found at the one-quarter-ahead horizon using real-time data but overall there is no evidence of predictability when revised data is used. Molodtsova (2008) further test the real-time predictability of 10 OECD countries. They have studied two specifications of the model: the single-equation framework and the panel estimation. Results show short term exchange rate predictability using panel methods. Molodtsova et al. (2011) tested the forecasting ability of the US dollar/ Euro exchange rate during the period 1999 to 2007 using real-time data. They found evidence of predictability with both one-quarter-ahead and longer horizon. Moreover, they found that the strongest evidence of predictability is from the simplest specification where the interest rate responds only to inflation and a measure of real economic activity (i.e. without interest rate smoothing and the real exchange rate).

Furthermore, these papers have also discussed how the choice of different types of data affects the out-of-sample performance of models with Taylor rule fundamentals. Molodtsova et al. (2008) concentrate on the USD/DM nominal exchange rate and found that in respect to monetary policy, the US obeys the Taylor principle regardless of whether revised or real-time data is used, but Germany only obeys the Taylor principle in the real-time case. In respect of out-of-sample exchange rate forecasting, the short-run exchange rate predictability only appears when real-time data is used. Molodtsova (2008) further divide the real-time data into two types: first-release real time data, which contains only new information about macroeconomic fundamentals and current vintage real-time data, which contains all the information in each vintage found that exchange rate forecasts with first released real time data does not performs better than current vintage real-time data.

Economic fundamentals have been included in Taylor rule models for exchange rate forecasting and includes: output gap, inflation gap, real exchange rate and interest rate differences. However, various speicifications have been considered and results are inconclusive. For example, Molodtsova and Papell (2009) have stuided 16 specifications of the Taylor rule exchange rate models with three measures of the output gap: output from a linear quadratic and a Hodrick and Prescott (1997) (HP) trend. They found the strongest results in the Taylor rule model with heterogenous coefficients, smoothing, symmetry and with a constant. Molodtsova et al. (2011) include unemployment as another variable in the Taylor rule and found the strongest evidence of predictability with a homogenous coefficents, non-smoothing and a symmetric Taylor rule model.[12] Engel et al. (2015) extended their panel forecast, but did not include either the real exchange rate or interest rate difference in its Taylor rule specification. Molodtsova and Papell (2012) does not include the real exchange rate in its Taylor rule forecasting regression. Galimberti and Moura (2013) found that using imposed restrictions such as homogenous coeffficients improve forecasting.

To sum up, we can draw some important conculsions on the existing exchange rate forecasting literature. Firstly, it is difficult to find an empirical economic model that consistently outperfoms a driftless random walk for the out-of-sample estimations. Forecasts work well for some currencies during certain sample periods but may not work well for other currencies or sample periods. Secondly, the more recent exchange rate models such as the Taylor rule model improves the forecasting ability

[12] Homogenous coefficients means two central banks respond to the same to changes in inflation, output gap etc. i.e. response coefficients are equal. Models with smoothing means Taylor rule interest rate only partially adjusts to its target within the period, i.e. there is a lagged interest rate differential appears in the Taylor rule equation. Symmetric means we does not include the real exchange rate in forecasting equation.

of the exchange rate. Thirdly, there is no conclusion on which specification of the Taylor rule works best, although adding other factors such as unemployment does seem to help. Last but not least, the success of the short-run exchange rate forecasting is a subject of debate. [13]

[13] More detail is discussed in Rogoff and Stavrakeva (2008).

# Chapter 3 A Review of the Exchange Rate and Monetary Policies

The exchange rate is an important variable for policy decisions, especially in a small open economy. Before the 1970s, the exchange rates were fixed according to the Bretton Woods system with a belief that exchange rate stability is essential for promoting trade and investment. However, the fixed exchange rate regime had become difficult to maintain when the capital accounts were liberalized. When the central bank, faced with massive outflows, tried to maintain the fixed exchange rate and exhausted the foreign exchange, the currency crisis resulted.[14] Moreover, the fixed exchange rate with capital mobility meant the loss of control in monetary policy. In a fixed exchange rate system, a country maintains the same interest rate as the reserve country. As a result, it loses the ability to use monetary policy to control outcomes in its domestic economy. The impossibility of having capital mobility, the fixed exchange rate, and independent monetary policy, is often called "impossible trinity."

Later, IMF has recommended a combination of free float and inflation targeting in order to lessen the probability of a currency crisis with stability of domestic prices. Inflation targeting is a framework that the inflation rate is to be contained within an announced range in the medium term. The central bank forecasts the future path of inflation and compares it with the target inflation rate (the rate the government believes is appropriate for the economy). The difference between the forecast and the target determines how much monetary policy has to be adjusted. A fluctuation within the range is allowed according to a shock to the economy. The demand or supply shock is partially accommodated with a commitment that the inflation rate in the future will be kept or brought back to the target range. With the medium term

[14] The other countries' currencies were pegged to the US dollar.

commitment to price stability, expected future inflation rate would not change even with some shocks. This “constrained discretion” framework combines two distinct elements: a precise numerical target for inflation in the medium term and a response to economic shocks (e.g. such as exchange rate fluctuations) in the short term. Inflation targeting are achieved using tools as interest rate changes. Because interest rates and inflation rates tend to move in opposite directions, the likely actions a central bank will take to raise or lower interest rates become more transparent under an inflation targeting policy. Advocates of inflation targeting think this leads to increased economic stability.

A purist view is that an inflation targeting central bank should not attempt to manage the exchange rate. The central bank should not pursue two objectives. However, time to time, the monetary authorities have intervened in the foreign exchange market, and have attempted to influence the exchange rate movement. Many inflation-targeting central banks are believed to have managed the exchange rate in an attempt to lessen the volatility of the exchange rate. For example, Australia have adopted inflation targeting and have intervened in the foreign exchange market time to time, although the frequency of interventions has declined substantially.

During the study period, Countries have adopted various combinations of an exchange rate regime and a monetary policy framework. A Summary of the exchange rate regime changes are shown in Table 3-1. The exchange rate regime varies from the hard peg to free float. The monetary policy framework ranges from no-independence to total independence. This chapter summarizes the exchange rate regimes and monetary policies used by each country studied in this thesis. This will help us to understand how the monetary policies in these countries have reacted to exchange rate changes and also help to explain exchange rate movements.

**Table 3-1 Exchange rate regime from 1975-2008**

| ***Country*** | ***Data Sample begins*** | ***Exchange Rate regimes (pre and post crisis)*** |
|---|---|---|
| ***US*** | 1975-2008 | Floating |
| ***UK*** | 1975-1990 | managed floating |
| | 1991-1992 | Semi fixed |
| | 1992-2008 | Free floating |
| ***Australia*** | 1975-1983 | Managed floating |
| | 1983-2008 | Free floating |
| ***Sweden*** | 1975-1977 | Fixed |
| | 1977-1992 | Managed floating |
| | 1992-2008 | Free floating |

## 3.1 United Kingdom

Managed floating was the exchange rate policy pursued in the UK from 1973 to 1990 and involved some intervention by the central bank to influence the exchange rate at a time when the government was still in control of interest rates. From 1975, after the collapse of the Bretton-Woods system of fixed exchange rates, government policies began to tighten by reduce demand for monetary in order to low inflation. And the exchange rate depreciated. This ended in 1977 and then the exchange rate began to appreciate until 1980. This appreciation of sterling was largely due to a sharp increase in the world oil price and unintended monetary tightening. [15] Government was committed to a policy aiming to reduce inflation by a high nominal interest rate and the currency appreciated to unsustainable high levels. The high value of the pound imposed financial difficulties on UK industry, especially on manufactory and export. The UK's international competitiveness fell dramatically.

[15] As the UK became an oil producer.

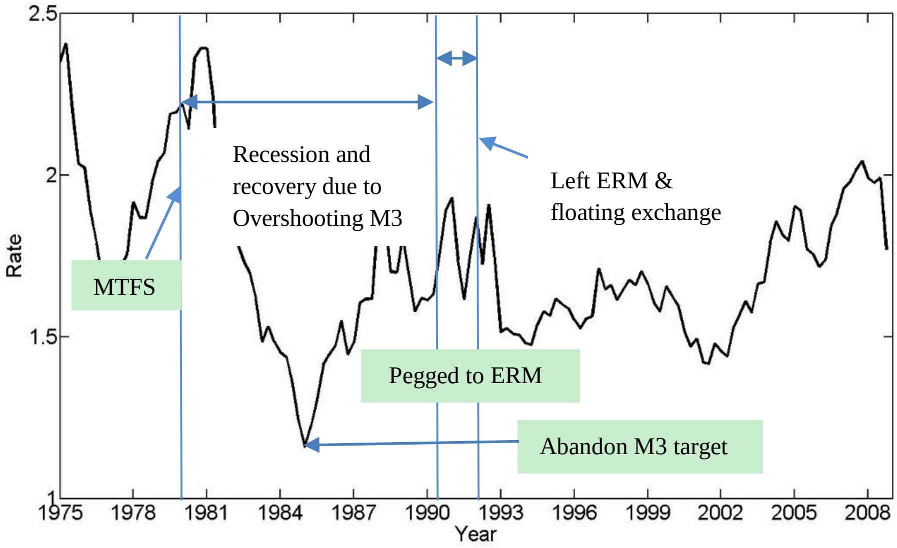
In March 1980, the government announced the Medium Term Financial Strategy (MTFS), a four year plan designed to reduce inflation and create conditions for sustainable economic growth. During 1982, the exchange rate becomes one of the indicators used in setting UK monetary policy. However, the centre piece of MTFS, £M3 growth target for money, is overshoot. The consumer boot out-weight any deflationary effects a stronger pound. The inflation rate did not fall to the expected four percent and it was at a heavy cost as the UK economy went into the worst recession since the 1920s. Therefore, ministers had successively downgraded its importance and in October 1985, the authorities abandoned the £M3 targeting. During the period 1985 to 1988, they tried to stabilize the exchange rate by intervening in the foreign exchange market and changing interest rates. However, evidence shows that they had difficulty in managing the exchange rate and inflation rose.

In October 1990, the UK joined the European exchange rate mechanism (ERM) to attempt to keep inflation under control.[16] The UK exchange rate was semi-fixed with interest rates set at a consistent level to keep sterling within the ERM bands. The appreciation in 1990 reflected the growing expectation of UK entry into the ERM. However, it joined at the wrong rate when the Bundesbank had raised interest rates to counteract any inflationary effects from German reunification. In order to maintain the exchange in within the ERM bands, the UK soon raised its interest rate and the pound appreciated against the dollar. Inflation is controlled but real interest rate was high. High real interest rate leas appreciation of pound. Trying to keep the pound at this high rate caused a deep recession with output and prices falling. Moreover, the high exchange rate attracted financial speculators (including George Soros) who foresaw the artificially high exchange rate was unsustainable. Therefore, despite a last minute increase in interest rates and massive foreign exchange market

[16] Within the ERM, Germany was dominant and other countries followed German interest rate policy because it had a good reputation as an inflation fighter.

intervention, the UK left the ERM on the 16th September, 1992. On leaving the ERM, the UK economy soon recovered and interest rates fell.

**Figure 3-1 the exchange rate between US dollar and UK pound 1975-2008**




*Note:* This is the nominal exchange rate obtained from DataStream, defined as the US dollar price per UK pound. An increasing in the graph represents an appreciation of the pound against the US dollar.

After September 1992, the UK operated a free floating exchange rate. The change of UK government in 1997 introduced a new framework. The government continued to set the inflation target, but the interest rate was controlled by a new Monetary Policy Committee at the Bank of England (BOE). They set interest rates in order to help meet the government's inflation target (Cobham, 2002). The changes in 1997 contributed to a slight boost to the economy and lead to a slight exchange rate appreciation. This pattern of the exchange rate was broadly maintained until 2008.

## 3.2 Sweden

The currency of Sweden is the Swedish Krona and it is controlled by the Sveriges Riksbank, the central bank of Sweden. The Sveriges Riksbank regulate foreign exchange controls through its Exchange Control Board.

In the 1970s the world economy was hit by two major shocks since the oil price was heavily increased in 1973 and in 1979. To handle this, Sweden chooses an expansionary domestic stability politic during 1974 until 1976 with the aim to avoid a depression.

The Swedish currency system during the period 1973-1977 was referred to as the 'Monetary Snake'. This is equivalent to a fixed rate regime relative to the German Mark—a dominating currency in the Monetary Snake. From the 1975s Sweden was hard hit by structural crises in manufacturing and a loss of competitiveness due to rising unit labour costs. In October 1976, the Frankfurt realignment of European exchange rates entailed a devaluation of the krona by 3 per cent against the mark. Even so, in 1976 the Swedish exchange rate appreciated against a weighted average of Sweden's trading partners, due to the decline of the US dollar and sterling. Therefore, the krona was devalued three times in the years 1976 and 1977. In the meantime of devaluation in August 1977, Sweden withdrew from the prevailing European system for exchange rate collaboration and directed its monetary policy to maintain a unilateral exchange rate target. The unit's effective rate depreciated by 10% and the Krona was pegged to a trade-weighted basket of 15 of Sweden's most important trading partners. The weights are proportional to Sweden's foreign trade with these countries, with the weight of the U.S dollar doubled to reflect its role as a transactions currency. However, the higher price and wage level of Sweden reduced its competiveness in foreign trade. The weights attached to the currencies in the basket were revised in 1981, 1982 and 1984 and the effective rate was devalued against the linked basket of currencies at 1981, 1982. In June 1985, the fluctuations in the spot rate were declared to be 1.5% around the benchmark value.

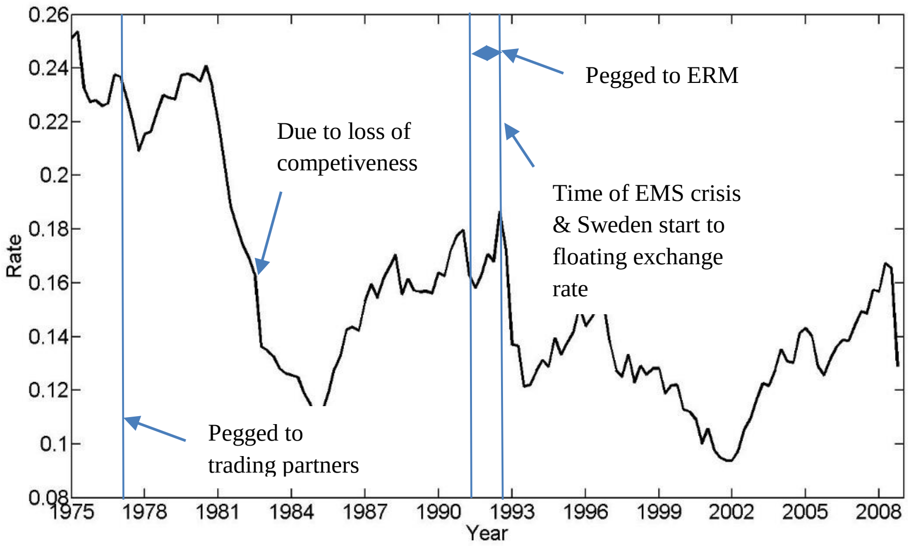
During the late 1980s, deregulations of the financial markets, and a tax system that encouraged debt-financed consumption stimulated the Swedish economy and it became overheated and inflation rose sharply. The Swedish central bank declared that there would not be a devaluation this time round. Instead, from mid-1991, the Krona was in the European Exchange Rate Mechanism (ERM). The basket was redefined to equal the European Currency Unit (ECU) instead of a trade-weighted basket.

After 1990, the Swedish economy experienced a deepening recession. This was due to the international economic downturn, the tax system which encouraged net savings, the abolishing of the investment allowance and outflowing of assets. Also the Swedish banking system collapsed due to excessive lending to the property sector, leading to the nationalisation of a number of Swedish banks. The Swedish economy exhibited a rapid decrease in economic activity and employment and inflation fell to a historical low rate of 2% in 1992. The overvalued krona led to expectations of a future devaluation. Despite the level of large foreign exchange intervention and adjusting the overnight interest rate by as much as 500 per cent.

In November 1992, the peg to ECU was broken and the Krona was forced to float. This lead to an immediate depreciation of the effective exchange rate by about 10%. The floating exchange rate system has brought a sharp increase in the volatility of the exchange rate, hitherto without any clear trend.

The Governing Board of the Riksbank Sweden announced it was applying inflation targets from 1995 on January 1993. The Krona was allowed to float freely based on supply and demand in the foreign exchange market, with the central bank having intervention rights. The economy had recovered substantially from 1993. This transition to inflation targeting and flexible exchange rate regimes brought changes in the conducting of monetary policy. During the fixed exchange rate regime, Riksbank adjusted the marginal rate (i.e. Riksbank's overnight rate in the interbank market) to achieve the short run target of stabilizing the exchange rate. However, with the shift to inflation targeting and a flexible exchange rate regime, the old monetary policy of interest rate management lead to inflationary pressures. Therefore, in June 1994, the Riksbank introduced a new interest rate policy.

**Figure 3-2 the exchange rate between US dollar and Swedish krona 1975-2008**




*Note:* This is the nominal exchange rate obtained from DataStream, defined as the US dollar per Swedish krona. An increase in the graph represents an appreciation of the Swedish krona against the US dollar.

In the new system, a two week repo rate is used instead of the marginal rate as the main instrument of monetary policy. [17] A lending and deposit rates were used as upper and lower bounds of a "corridor" within which the repo rate could move. This provide a flexible system for policy implement and signal monetary policy in longer-run.

[17] The repo rate is the rate at which securities with a maturity of one or two weeks are bought or sold by the Riksbank.

Due to the recession in continental Europe, economic activity in Sweden slowed during the second half of 1995. The krona depreciated sharply and reached a low in April 1995. However, since the summer of 1995, confidence in the Swedish economy and in Swedish policy seems to have improved. The krona has become stronger with about an 18 percent appreciation since April 1994. Both long and short rates of interest have fallen and inflation had come down from four percent in early 1995 to around 2 percent. In July 1996, the Riksbank shortened the maturity of its repos to one week. Despite the creation of the Euro in 1999, Sweden has retained the Krona. The depreciation until 2002 is due to the appreciation of dollar. The appreciation of krona after 2002 is caused by the strong rise in interest rate difference against US.

## 3.3 Australia

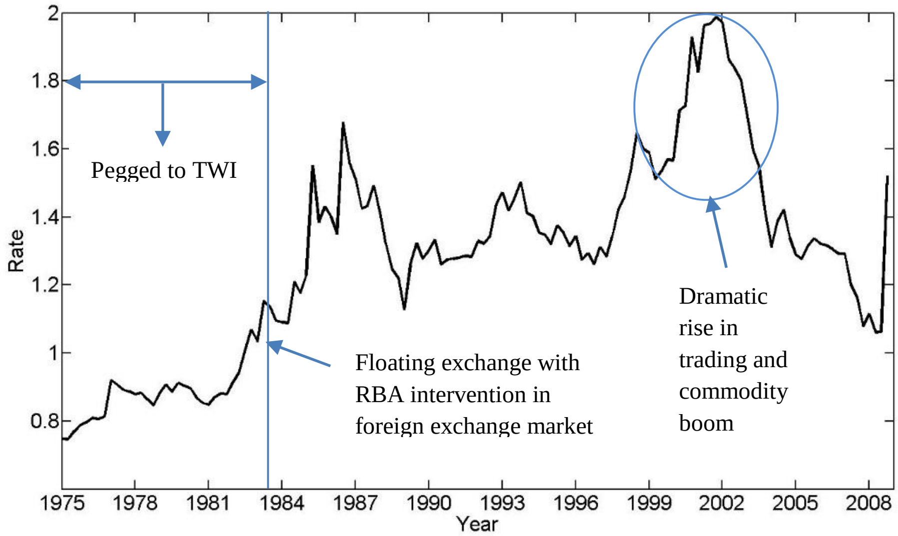
The currency of Australia is the Australian dollar. The reserve bank of Australia is Australia's central bank. It conducts monetary policy and manages the foreign exchange rate reserves.

After the breakdown of the Bretton Woods system in 1973, Australia moved to a managed floating system in order to reduce the effect of exchange rate fluctuations. The Australian dollar was measured relative to a basket of currencies called the trade weighted index (TWI). [18] This exchange rate was set daily by the Reserve Bank of Australia (RBA). The system continued until the Australian dollar was floated. At the end of 1983, Australia adopted a floating exchange rate system. The exchange rate became market-determined with the RBA retained discretionary power to intervene in foreign exchange markets.

[18] The trade weighted index (TWI) measures the Australian dollar against a basket of 23 currencies of Australia's main trading partners. The weight is measured by their significance to Australia's trade flow. It is a more comprehensive measure of the purchasing power of the Australian dollar.

The highest valuation of the Australian dollar relative to the U.S. dollar during the period studied is during the period of the managed floating system. In 1975, the exchange rate was around US$1.33. The Australian dollar had a depreciating trend until Q4 2001. Between 2000 and 2008 the trend in the Australian dollar was for an appreciation against the value of the dollar. In Q3 2008, it reached a high of US$0.94, but then the value fell significantly from this high until the end of 2008. There are a number of factors contributing to the appreciation between 2001 and 2008. A dramatic rise in the terms of trade was the major cause. During this time, there was a commodity boom which raised Australia's commodities export prices. Australia is the main source of raw materials for emerging countries, particularly the growing Chinese economy. The quick development and rising demand for raw materials from these countries increased the export prices of Australia's raw materials. Also, Australia attracts a lot of foreign investment through its higher interest rate which also leads to an appreciation of the exchange rate (Garton et al. 2012).

**Figure 3-3 the exchange rate between US dollar and Australia dollar 1975-2008**




*Note*: This is the nominal exchange rate obtained from DataStream, defined as the US dollar per Australian dollar. An increase in the graph represents an appreciation of the Australia dollar against the US dollar.

## 3.4 United States

In the United States, The Federal Reserve, working with other Central Banks, has a major influence on all questions of currency policy. This include regulating domestic money and credit policy and control of foreign lending. In 1971, the US abandoned the gold convertibility of dollar and formed a flexible exchange rate regime. Until now, The U.S. dollar has been the most commonly used currency in international transactions.

Since the great inflation of the 1970s, the Federal Reserve conducts monetary policy by focusing on the cost of money and credit as proxy by an interest rate. During the 1970s, the exchange rates against G5 countries fluctuated widely and inflation rates accelerated. The high inflation was a result of increasing money stock when the Fed attempted to match money market conditions, the federal fund rate and three-month Treasury bill rate, with inflation. With more money pumping into the system to keep interest rates down, inflation pressures were raised. During the late 1970s, the dollar depreciated. This was a result of excessive U.S. monetary expansion. In October 1979, The Fed announced a change in its open market procedures in order to stop inflation. They gradually tightened monetary policy and let interest rates rise. These actions reversed the downside movement of the dollar and lead to a significant appreciation between 1980 and 1982. The increase in the value of the dollar and interest rate brought about negative effects on various interest rates sensitive or exchange rate sensitive sectors, which lead to a recession. A recovery from the recession began in 1983 when the Fed shifted to an expansionary policy. The authorities began to cut income tax and the demand for funds increased and the dollar appreciated. During the period 1984 to 1985, the dollar not only appreciated but at an accelerated rate.

After 1985, the dollar started to depreciate against the other G5 countries. In September 1985, the meeting between G-5 countries’ finance ministers and central bank governors agreed to bring the dollar down. This is the so-called Plaza

Agreement on exchange rates. From then on, the interest rate advantage of dollar assets was reduced and the dollar depreciated. Afterwards Exchange rate intervention had been more often been used as a policy instrument. Between 1985 and 1995, intervention was undertaken by the Fed, with coordination of central banks, to push the dollar into an acceptable range and stabilize the exchange rate. However, since the mid-1990s, the Fed has generally shifted its focus from foreign exchange intervention to an inflation objective, leaving the highly effective foreign exchange market to determine rates.

Early in 1994, the Fed shifted to a contractionary policy, reduced the money supply and raised interest rates. By March 1997, inflation had fallen to 2.4%. The Fed started to raise the interest rate whilst inflation remained below 2%. In 1998, the US government was concerned whether its growth would be affected by the Asian economic recession and slow growth in Europe. So the authorities slightly reduced the federal fund rate. From 1999, with inflation under control, the authorities started to reduce the federal funds rate in order to stimulate the economy. During the period between 1995 and 2002, the exchange rate appreciated. The last rate cut was in mid-2003. In mid-2004, the growing US economy raised concerns about inflation, so the Fed increased interest rates. During the recession of 2008, the US was threatened with deflation, the Fed was sought all possible options in trying to moderate the recession and keep financial markets running smoothly, this required steep cuts in interest rates and eventually quantitative easing.[19]

[19] Quantitative easing is a type of monetary policy used by central bank to stimulate the economy when standard monetary policy become inefficient.

# Chapter 4 Estimation of a Taylor Rule Exchange Rate model with a Wealth Effect[20]

## 4.1 Introduction

In this study, I have developed the model of Molodtsova and Papell (2009) in specifying a two-country model of the open economy, in which monetary policy in the home and foreign economies are described by Taylor Rules. The interest rate reaction functions are of a similar form to Taylor (1993), however additional variables have been included in the model to capture the wealth effect.

The contributions of this chapter are: firstly, various specifications of Taylor rule models incorporating stock prices and house prices will be assessed. According to the extensive literature, there has been no attempt to use the Taylor rule framework to investigate the relationship between asset prices and the exchange rate. Stock prices, as a proxy for the wealth invested in stock markets, have been extensively analysed in the context of exchange rate models. However, house prices have not been previously used in exchange rate model, although its importance in formulation of monetary policy has been proven in the past literature. As Case *et al.* (2005) suggest both have varying degrees of influence on the macro-economy, with housing being the most significant. Given the importance of the exchange rate to the economy as a whole, especially in the conduct of monetary policy, it is important to understand what factors determine its movements and how it interacts with other financial markets.

[20] Some of the material based in this chapter has been presented at the 54th Euro Working Group for Commodities and Financial Modelling conference, 2014, Milano, Italy. I would like to thank participants at the conferences for their helpful and constructive comments.

In Section 2.5.4 the unrealistic assumption about the data used in measure Taylor rule has been discussed. It is clear that real-time data should be used for Taylor rule estimation and forecasting. In order to evaluate the performance of Taylor rule based exchange rate with more accuracy. Data revision problems in output gap measure has been solved by using quasi-real time data in the construction of trend.

Moreover, this chapter makes a renewed investigation of the empirical relevance of the Taylor rule in modelling exchange rates. The Taylor rule has become popular in exchange rate studies since the second half of the 2000s. However, the previous studies in this area have, to a large extent, ignored both the time series properties of the included variables and the properties of the estimated models (e.g. Molodtsova and Papell, 2009; Galimberti and Moura, 2013; Ince, 2014). This is important especially in the case when there are strong indications of the variables in the regressions having unit roots and /or structural breaks. Phillips (1988) argued that if variables are integrated of order one (i.e. have a unit root or are non-stationary), then forming static regressions using levels can lead to spurious regressions.

The purpose of this chapter is to investigate the empirical relevance of the Taylor rule in modelling exchange rate movements for the U.S. exchange rate with respect to the Australian dollar, Swedish krona and British Pound sterling. Focus is put on the time series properties of the variables and the relevance of the Taylor rule in conjunction with wealth effects in modelling exchange rates. As noted previous studies such as Molodtsova and Papell (2009) have concentrated on forecasting the model and not reported the regression results, this chapter adds to that study by including the estimation results, with particular emphasis on the role of the wealth effect. This chapter finds a significant wealth effect in the studied countries, suggesting that the wealth effect is an important factor in modelling exchange rates and needs to be considered as an additional component in these empirical models. Moreover, results from the Lee Strazicich test show all variables become stationary after taking into account structural breaks. Therefore, by accounting for any structural breaks with dummy variables, we can form regressions on the exchange rate using variables in their level forms.

The chapter is organized as follows. Section 2 is the literature review on wealth studies. Section 3 explains the adopted Taylor rule exchange rate models; Section 4 elaborates on the estimation methodology, Section 5 describes data for the countries in this study. Section 6 presents estimation results and explains the reason for the breaks and Section 7 concludes.

## 4.2 Literature Review

### 4.2.1 The Importance of the Wealth Effect

Wealth effects refer to the link between the level of an individual's personal wealth and their decisions about how much to spend or save on goods and services. When the value of a stock portfolio or house rises, investors feel more confident and secure about their wealth and this will cause them to spend more. The importance of wealth effects has been indicated in many policy and exchange rate studies. Some of the relevent works are discussed below.

Asset prices, mainly through wealth effects on real economic varaibles such as consumption, investment and stability of the financial sector, might have a direct impact on economic activity and therefore have often been used as a proxy for the underlying state of the economy (Grant and Peltonen, 2008).

A number of studies have highlighted that wealth effects can enhance monetary policy. An ealier work of regarding this can be found in Friedman (1988). By using data from the US, he discussed the need for real stock prices to stabilise money demand equations. According to Friedman (1988), changes in stock price might have two effects on demand for money. The first is called a wealth effect, that is a rise in stock prices increases the demand for money.[21] The second is known as the subsititution effect which works in the oppsite direction.[22] Later, after the work originally by Taylor (1993), who first proposed a formulation for linear monetary policy rules by setting the short term interest rate. A number of papers have attempted to create a more effective interst rate rule by considering the effect of wealth factors in the conduct of monetary policy. For example, Benchimol (2007) studied the impact of wealth effects on monetary policy, where the monetary policy is represented by a Taylor rule. They conclude that monetary policy becomes more accommodating after considering wealth effects. Cecchetti et al. (2000) suggest that the central bank is likely to achieve a superior performance (i.e.stable inflation and output) by including not only inflation and the output gap in policy formulation, but also asset prices. Semmler and Zhang (2007) argued in the case of open econmies that central banks should systematically and explicitly respond to asset price movements. Castro and Sousa (2012) accessed whether central banks should react to household wealth (i.e financial and housing wealth)  in both linear and nonlinear interest rate reaction functions. Using quarterly US, UK and Euro area data, they find evidence supporting the idea that wealth composition is important for the formulation of monetary policy. In particular, the European Central Bank (ECB) and the Federal Reserve Board (Fed) focused more on financial wealth whereas the BoE focused more on the housing wealth.

Moreover, the importance of the wealth effect is indicated in the exchange rate literature for various reasons. One hypothesis made by Dimitrova (2005) stated that when stock portfolios and house prices increase in value, investors tend to spend more. If demand is growing faster than the domestically-produced supply, the heightened demand for imports will increase demand for foreign currencies,

[21] For wealth effect, a rise in stock price will lead to a high money-to-income ratio. This is because individuals want to align their money holding with increased perceived wealth.

[22] With substitution effect, rise stock price will rise return expectations of equity investment. This will make the equity investment relative more attractive than money holding.

appreciating the foreign currencies relative to the domestic currency. If wealth effects influence monetary policy, then it may also affect the exchange rate, especially in the Taylor rule model. Roberts (2001, p.2) stated: ‘if monetary actions are found to affect wealth significantly, the explicit inclusion of wealth variables in models relating monetary actions to institutions and individual behavior should reduce statistical bias and increase the explanatory ability of econometric models.’

Among various forms of household wealth, fluctuations in the stock market and in house values over the course of recent years have received the most media attention and consideration in economic policy debates.

### 4.2.2 Housing as a Wealth Effect

Housing is generally believed to be the largest investment for households. Fluctuations in residential property prices tend to have a big wealth effect. There are a number of empirical papers which have examied the housing wealth effect. Mishkin (2007) finds evidence of a large wealth effect from housing. Case et al. (2005) not only find a significant wealth effects from housing, but also find that the wealth effect from housing is larger than the wealth effect from stock prices. They show that a sharp decline in house prices had a much bigger impact on output growth than equity prices. The wealth effect from housing is so important that the Financial Sector Assessment Program, which was introduced by the IMF and the World Bank in 1999, advocates the inclusion of real estate prices in the recommended set of financial soundness indicators (Glindro et al., 2011). Policymakers at the Fed employ a model which assumes large and singificant housing wealth effects when formulating policies.

There are good reasons why we should include house prices as an explanatory variable in exchange rate models. Firstly, the housing wealth effect is an important component of the overall wealth effect since housing represents a major asset in households’ portfolios. Secondly, housing wealth affects money demand and the policy rule, which are also important determinants of the exchange rate. Vickers (1999) states that asset prices could be a part of monetary policy objectives and/or a part of the information used to follow these objectives. His argument has been supported by the crisis in the 2000s. In the case of the pre-crisis 2000s, both inflation and the output gap as a measure of monetary policy may remain stable, but some assets prices (e.g. the level of housing investment) were too high and produced the potential to trigger major macroeconomic adjustments later on. Engel and West (2006) have formulated an exchange rate model from Taylor type monetary policy rules and found it gave a good explaination about exchange rate movements. So if housing wealth has the potential to be added to the Taylor rule, it would equally have the potential to be added to Taylor rule exchange rate models.

To my knowledge, there are no studies in the literature analysing the direct link between exchange rates and the wealth effect of housing. The macroeconomic models typically posit a wealth effect through which increases in the value of the housing stock raise consumption demand: when house prices rise, consumers experience an increase in wealth, and increase spending accordingly. However, Glindro et al. (2011) mentioned the relationship between the two without a detailed empirical analysis. When a countries exchange rate is strong relative to a trading partner, the appreciated exchange rate would exert a positive influence on property market prices. This is because when a country'exchange rate is strong, investors feel more financially secure as their currency has enhanced buying power on the international stage. Therefore, exchange rate appreciation is normally associated with housing booms, especially in countries where foreign investments play an important role (Glindro et al., 2011). Moreover, an increase in house prices is typically associated with market-wide low interest rates. A lower interst rate will leads an outflow of capital from those countries with the higher real rates of interest. Therefore, there will be a decrease in demand for these currencies, and they will depreciate relative to currencies of countries whose avalible real rate of return is higher.

### 4.2.3 The Exchange rate and Stock prices

Over recent years, the study of the interactions between the national stock prices and exchange rates has become of increasing interest. The relationship between stock prices and exchange rates became closer because of the increasing levels of capital flows between international financial markets and the relaxation of exchange rate regimes, (Solnik, 1987).

In the literature, there are two main theories that link the relationship between stock prices and exchanges. The two approaches work in opposite ways to each other. According to the traditional approach first discussed by Dornbusch and Fisher (1980), currency deprecation will increase the competitiveness of domestic firms' exports therefore increasing profit. This increase in corporations' profit will be reflected in the stock market by a rise in their stock price. A similar idea has also been discussed in Solnik (1987). Another popular approach is known as the portfolio adjustment approach. According to the portfolio approach, the change in the stock market led to changes in the exchange rate due to investors' inflow and outflow of capital. If stock prices increase persistently, local investors will sell their foreign assets and buy domestic assets. This will increase the demand for the domestic currency and put an upward pressure on the domestic currency. Moreover, the wealth of domestic investors will also increase. This will lead to an increase in the demand for money and ultimately higher interest rates. The high interest rate will encourage capital inflows and lead to currency appreciation. Researchers have employed this method for exchange rate and stock price studies including Frankel (1983a), Lewis (1988), Smith (1992) and Dornbusch (2011).

The interaction between stock prices and the foreign currency market has been the subject of much academic debate and empirical analysis over the past years. Overall, the results are mixed as to the significance and the direction of influence between stock prices and the exchange rate. Among the studies on the relationship between stock prices and exchange rates, some have concentrated on the direct relationship between stock prices and exchange rates, while others have used specific models such as the monetary models, portfolio balance models and general cointegration models. For example, Solnik (1987) suggested that stock prices reflect expectations about future ecnomy activity. In his study, stock returns are used as proxies for changes in economic activity to test the relationship between exchange rates and economic activity. He employed a regression anaylsis on monthly and quarterly data from 1973 to 1983 for eight industrialized countries and found a negative relationship between real domestic stock returns and real exchange rate movements. However, for monthly data from 1979 to 1983, he observed a weak but positive relationship between the two varaibles. Granger et al. (2000) and Morley (2007) incorporated stock prices into the monetary model to investigate the relationship between equities and exchange rates. The result suggests a stable long-run and short-run relationship. Bahmani-Oskooee and Sohrabian (1992) using a portfolio balance model test whether stock prices have an impact on exchange rates using US data. Their result show that in the short-run stock prices have a significant effect on the exchange rate. however, in the long run, this relationship disappears.

Smith (1992) applied the portfolio balance model to the German mark-U.S. dollar and Japan Yen-U.S. dollar exchange rate. His result showed a strong impact from stock (equity) prices on exchange rates. More importantly, he pointed out that part of the reason for the weak relationship between exchange rates and stock prices in previous portfolio balance studies is due to the choice of the asset set. In previous studies, the asset choice set is restricited to nominal government bonds or bonds and money. He cites as examples studies by Branson, Haltunnen and Masson (1977) and Diebold and Pauly (1988). All of which use government bonds or government bonds and money as the only outside assets in the exchange rate equation.[23] In order to support his argument, he chooses explanatory variables that include the value of equities in addition to government bonds and money in his exchange rate model. By

[23] Outside assets are assets of a natural or legal person that are not a liability of some other natural or legal person(s).

using data from the United States, Germany and Japan, he concludes that equities play an important role in empirical models of the exchange rate. By contrast, the impact of government bonds and money on exchange rates is quite weak. When eqities were excluded, the estimating equations show evidence of serial correlation and parameter instability, both of which suggest model misspecification due to omitted variables. Their conclusion in general explained results found in previous studies by Frankel (1983a) and Lewis (1988) among others.

## 4.3 Theoretical Model

### 4.3.1 A Modified Taylor Rule Model

According to Molodtsova and Papell (2009), the simplest monetary policy rule postulated by Taylor (1993) stated that the central bank set the interest rate in response to changes in inflation and the output gap.

$$i_t^* = \pi_t + \delta(\pi_t - \pi_t^*) + \gamma y_t + r^* \tag{4-1}$$

where $i_t^*$ is the target for the short-term nominal interest rate, $\pi_t$ is the inflation rate, $\pi_t^*$ is the target level of inflation, $y_t$ is the output gap, or percent deviation of actual real GDP from an estimate of its potential level, and $r^*$ is the equilibrium level of the real interest rate.

In addition to this original specification which only includes inflation and the output gap, this study extends the model through the addition of a variable representing the effects of wealth on the baseline equation, as used in other studies such as Semmler and Zhang (2007).

$$i_t^* = \pi_t + \delta(\pi_t - \pi_t^*) + \gamma y_t + \beta w_t + r^* \tag{4-2}$$

where $w_t$ is the asset price;

The parameters $\pi_t^*$ and $r^*$ in equation (4-2) can be combined into one constant term $\mu = r^* - \delta\pi^*$ which leads to the following equation:

$$i_t^* = \mu + \lambda\pi_t + \gamma y_t + \beta w_t \tag{4-3}$$

where $\lambda = 1 + \delta$;

Later, study of Clarida, Galí, and Gertler (1998), Ball (1999) and Taylor (2001, 2002) suggest that the original Taylor rule should be modified for a small open economy by including the real exchange rate in the interest rate rule.[24] In this spirit, we consider our baseline specification for monetary policy-makers' interest rate as:

$$i_t^* = \mu + \lambda\pi_t + \gamma y_t + \beta w_t + \phi q_t \tag{4-4}$$

where $q_t$ is the real exchange rate.

A lagged interest rate is usually included in estimating the Taylor rule to account for the fact that the Fed follows the Taylor rule but adjust smoothly to its target level. The actual observable interest rate $i_t$adjusts partially to the target rate as follows:

$$i_t = (1 - \rho)i_t^* + \rho i_{t-1} + v_t \tag{4-5}$$

where $\rho$ denotes the degree of interest rate smoothing and $v_t$ the error term also known as the interest rate smoothing shock.

Substituting (4-4) into (4-5) gives the following equation for the actual short-term interest rate:

[24] Central bank of small open economy often sets a target for the level of the exchange rate to ensure PPP holds in the long run.

$$i_t = (1-\rho)(\mu + \lambda\pi_t + \gamma y_t + \beta w_t + \phi q_t) + \rho i_{t-1} + v_t \tag{4-6}$$

Taking the US to be the domestic country and the equation (4-6) as the interest rate reaction function for the foreign country; the monetary policy reaction function for the US is the same as equation (4-6) with $\phi = 0$.

### 4.3.2 A Taylor Rule Exchange Rate Model

To derive the Taylor rule based exchange rate equation, we construct the implied interest rate differential. Let ~ denote variables for the foreign country; the interest rate differential is constructed by subtracting the Taylor rule equation for the foreign country from that for the domestic country, the US.

$$i_t - \tilde{i}_t = \psi + \left(\psi_{u\pi}\pi_t - \psi_{f\pi}\tilde{\pi}_t\right) + \left(\psi_{uy}y_t - \psi_{fy}\tilde{y}_t\right) + (\psi_{uw}w_t - \psi_{fw}\tilde{w}_t) - \psi_q\tilde{q}_t + \rho_u i_{t-1} - \rho_f\tilde{i}_{t-1} + \eta_t \tag{4-7}$$

where $u$ and $f$ are coefficients for the U.S. and foreign country respectively; $\psi$ is a constant, $\psi_\pi = \lambda(1-\rho)$, $\psi_y = \gamma(1-\rho)$ and $\psi_w = \beta(1-\rho)$ for both countries, and $\psi_q = \phi(1-\rho)$ for the foreign country.

In order to derive the exchange rate equation, the simplest and most direct way is to assume the expected rate of exchange rate depreciation is proportional to the interest rate differential:

$$E(\Delta s_{t+1}) = \beta(i_t - \tilde{i}_t) \tag{4-8}$$

where $\Delta s_{t+1}$ is the logarithm of the difference of the nominal exchange rate; specified as the home currency price of foreign currency, and $E$ denote the expectation operator. Assuming the Interest Rate Parity (UIRP) held with rational expectation, then $\beta = 1$ , and we have the Taylor rule exchange rate equation:

$$\Delta s_{t+1} = \psi + \psi_{u\pi}\pi_t - \psi_{f\pi}\tilde{\pi}_t + \psi_{uy}y_t - \psi_{fy}\tilde{y}_t \\ + \psi_{uw}w_t - \psi_{fw}\tilde{w}_t - \psi_q\tilde{q}_t + \rho_u i_{t-1} \\ - \rho_f\tilde{i}_{t-1} + \eta_t \qquad (4\text{-}9)$$

where $s_t$ is the natural log of the U.S. nominal exchange rate, defined as the US dollar per unit of foreign currency, so that an increase in $s_t$ is a depreciation of the US dollar.

This is based on the Dornbusch (1976) overshooting model which connects the monetary policy reaction function to exchange rate behavior using the UIRP. It is frequently used in the Taylor rule exchange rate models (for example, Galimberti and Moura, 2013; Moura, 2010; Molodtsova, 2008 and Jian and Wu, 2009 among others). Under the assumption of UIRP, an increase in the interest rate would cause an immediate appreciation of the exchange rate followed by an actual and forecast depreciation. So an increase in inflation, output gap and/or wealth effect will increase the country's interest rate, leading to expected exchange rate depreciation.

However, papers by Molodtsova et al. (2008) and Molodtsova and Papell (2009) have questioned the UIRP assumption. They point out that there is no reason to believe the coefficient in equation (4-9) will match the coefficient from the estimated Taylor rule (i.e. equation (4-7)). Firstly, the empirical work on UIRP found that the UIRP does not hold in the short run. [25] Moreover, from the recent literature on the carry trade and forward premium anomaly, it is unclear if the coefficient on the interest rate differential in equation (4-8), i.e. $\beta$, is positive or negative.[26] Thirdly,

[25] Examples are Chinn (2006) and Eichenbaum and Evans (1995).

[26] Carry trade, refer to currency carry trade is an uncovered interest rate arbitrage. This is a strategy in which investor borrows low-yielding currencies and lend high-yield currencies. Forward premium

there is strong evidence that interest rates do not adjust to their target levels completely within the period. For these reasons, different assumptions about the coefficient signs of the exchange rate model are made by different studies. Table 4-1 provide a summary of these assumptions.

**Table 4-1 Assumptions of Taylor Rule Exchange Rate Model**

| **Model** | **Assumption** | **Relationship between exchange rate and fundamentals** |
|---|---|---|
| Dornbusch (1976) | Overshooting model: exchange market will overact to a monetary changes in the short run | + |
| Molodtsova & Papell (2009) | Investors will systematically under estimate the persistence of interest rate shock | – |
| Molodtsova *et al.* (2008) | Complicated relationship between fundamentals and exchange rate | Undefined |

For example, Molodtsova *et al.* (2008) suggest that the interest rate has a complicated relationship with exchange rates. Factors such as increases in the U.S. inflation rate above its target, output gap above its target and other variables in the Taylor rule model will cause the Fed to raise the interest rate. In addition, this action will also create an expectation that the Fed will raise the interest rate further in the future. However, the increase in the interest rate does not necessarily cause an expected depreciation of the exchange rate. Similarly, the expectations of further increases in interest rates will not definitely lead to an expected exchange rate appreciation, like

anomaly refer to the tendency for currencies with high interest rates to appreciate against currencies with lower interest rates. The empirical result that the exchange rate is negatively correlated with the lagged forward premium is often referred to as the forward bias puzzle. Froot and Thaler (1990) have shown that the estimation of β, using exchange rates against the US dollar, are often statistically insignificantly different from zero and closer to minus unity.

in the UIRP. Therefore, it is not possible to define the sign of for the coefficient of a specific variable in equation (4-9) as it is not known in advance how exactly changes in interest rates will impact exchange rates. Therefore, the exchange rate equations in their study are estimated without any restriction on the signs or magnitudes of the coefficients.[27]

Molodtsova and Papell (2009) estimate the exchange rate equation by imposing restrictions on the sign of the coefficients of the independent variables. They argue that an increase in the interest rate will lead to a sustained exchange rate appreciation. The idea is based on the empirical results of Gourinchas and Tornell (2004) and Bacchetta and Van Wincoop (2010). Both of them show that if investors systematically underestimate the persistence of interest rate shocks, then an increase in the interest rate can cause sustained exchange rate appreciation. Based on this theoretical evidence, Molodtsova and Papell (2009) assume that an increase in inflation, output gap and /or wealth effect will increase the interest rate of the country, causing an immediate appreciation in the exchange rate.

Under the above predictions, any microeconomic shocks that cause the Fed to raise the federal funds rate will produce an immediate and forecast dollar appreciation. And any events that cause the foreign central bank to raise its interest rate will lead to both immediate and expected dollar depreciation. By combining these predictions with equation (4-7), we get an exchange rate equation based on the Taylor rule:

$$\begin{aligned}\Delta s_{t+1} = \alpha - \alpha_{u\pi}\pi_t + \alpha_{f\pi}\tilde{\pi}_t - \alpha_{uy}y_t + \alpha_{fy}\tilde{y}_t \\ - \alpha_{uw}w_t + \alpha_{fw}\tilde{w}_t + \alpha_q\tilde{q}_t - \alpha_{ui}i_{t-1} \\ + \alpha_{fi}\tilde{\imath}_{t-1} + \eta_t\end{aligned} \tag{4-10}$$

[27] Clarida and Waldman (2008) construct a model that combines a Taylor rule with a Phillips curve to derive conditions under which a surprise increase in U.S. inflation will lead to appreciation of the exchange rate.

The reversal of the signs between equation (4-9) and equation (4-10) reflects the predictions that anything that causes the interest rate in the U.S. to be higher than that of the foreign country will lead to an immediate and sustained appreciation of the US dollar (i.e. $s_t$ decreases). The magnitudes of the coefficients of the two equations are different because we do not know how much the change in the interest rate differential will affect the exchange rate. It also does not require the interest rate smoothing shock $\eta_t$ to satisfy any assumption in our estimation.

Based on the studies of Molodtsova and Papell (2009) and Molodtsova (2008) and considering the lack of empirical support for UIP,[28] there is no reason to believe that the coefficients in equation (4-10) will match the coefficients implied by the estimated Taylor rule exchange rate model. Since we do not know the extent to which changes in the interest rate differential affect the exchange rate, we estimate our forecasting equations without imposing any restrictions on the signs and magnitudes of the coefficients.

### 4.3.3 Specification of the Taylor Rule Exchange Rate Forecast Model

A number of models are considered in this section. A general specification of the models takes the following form

$$\Delta s_{t+1} = \alpha_m + \beta_m X_{m,t} + \eta_{m,t+1} \tag{4-11}$$

[28] Kearns and Manners' (2006) suggest that although the UIP condition has been argued by many to be an empirical failure (e.g. Chinn, 2006), it might work reasonably well in a small economy, such as the three of those used here, as changes in interest rates in small economies are unlikely to have an impact on foreign interest rates and hence affect the exchange rate. Moreover, UIP connects expected changes in exchange rates to interest differentials, which has been proven to be an important and useful transmission channel connecting exchange rate changes endogenously to monetary policy (Molodtsova & Papell, 2009).

The econometric analysis in this study uses equation (4-11) as a benchmark. $m$ is the index of these models, $\Delta s_{t+1}$ is the change in the log of the nominal exchange rate determined as the domestic price of foreign currency. $X_{m,t}$ contains economic variables that are used in model $m$.

Based on different assumptions and specifications about the coefficients, we will study 16 different models. The assumptions and specifications are listed below:

- Specification 1: $X_{1,t} \equiv [\, \pi_t - \tilde{\pi}_t \quad y_t - \tilde{y}_t \quad w_t - \widetilde{w}_t \,]$
- Specification 2: $X_{2,t} \equiv [\, \pi_t - \tilde{\pi}_t \quad y_t - \tilde{y}_t \quad w_t - \widetilde{w}_t \quad \widetilde{q}_t \,]$
- Specification 3: $X_{3,t} \equiv [\pi_t - \tilde{\pi}_t \quad y_t - \tilde{y}_t \quad w_t - \widetilde{w}_t \quad i_{t-1} - \tilde{\imath}_{t-1} \,]$
- Specification 4: $X_{4,t} \equiv [\, \pi_t - \tilde{\pi}_t \quad y_t - \tilde{y}_t \quad w_t - \widetilde{w}_t \quad \widetilde{q}_t \quad i_{t-1} - \tilde{\imath}_{t-1}]$

Specification 1 is the benchmark model. Specification 2 takes into account the real exchange rate. Specification 3 and 4 include the lagged interest rate to taken into account the potential interest rate smoothing by the central bank.

- Assumption 1: Asymmetric or symmetric: where symmetric means that the central bank does not target the exchange rate $\phi = \psi_q = 0$;
- Assumption 2: smoothing ($\rho_u \neq 0$ and $\rho_f \neq 0$) and without smoothing ($\rho_u = \rho_f = 0$).
- Assumption 3: homogeneous coefficients: when U.S. and foreign central banks have the same responses to changes in inflation, the output gap, the wealth factor and their smoothing coefficients are also equal ( $\psi_{u\pi} = \psi_{f\pi}$, $\psi_{uy} = \psi_{fy}$, $\psi_{uw} = \psi_{fw}$ and $\rho_u = \rho_f$ ); heterogeneous coefficients: when the response coefficients are different.
- Assumption 4: when taking different representations of the wealth effect: stock prices and house prices.

## 4.4 Methodology

### 4.4.1 The output gap measurement

The output gap is usually defined as the deviation of actual output from potential output. Traditionally, potential output is measured by an estimated trend. The output gap is thus the deviation of output from its trend.

There are several ways to estimate potential output and thus the output gap. For example, the linear trend, the quadratic trend and the Hodrick-Prescott (HP) filter.[29] Often these approaches lead to similar output gap estimates (see Gerlach and Yiu, 2004). Among these, the HP filter is the most widely used approach for determining the output gap, especially in Taylor rule and exchange rate studies (e.g. Adema, Y., 2004; Molodtsova, 2008; Molodtsova and Papell, 2009; Gloria, 2010; Brüggemann and Riedel, 2011). One of the key advantage of the HP filter is the good quality of its results. Molodtsova and Papell (2009) compare forecasting results based on different output gap measurements and found that the output gap derived from the HP filter gave better forecasting result than the others. Therefore, in this study, potential output is construct by using HP-filtered GDP.

The HP filter of Hodrick and Prescott (1997) is a popular technique for extracting a cyclical component. This was originally developed as the solution to the problem of minimising the variation in the cyclical component of an observed time series, subject to a condition on the smoothness of the trend component, lambda. Given a time series, $y_t$, the HP filter will decompose it into a trend component $y_t^p$ and a cyclical component $y_t^c$:

$$y_t = y_t^p + y_t^c \qquad (4\text{-}12)$$

[29] The linear trend is the oldest and simplest of these models and the quadratic trend is a popular simple extension of linear model.

The trend component is obtained by minimising actual output (y) around trend output ($y_t^p$) subject to a constraint, i.e.

$$min \sum_{t=1}^{T} (y_t - y_t^p)^2 + \lambda \sum_{t=2}^{T-1} [(y_{t+1}^p - y_t^p) - (y_t^p - y_{t-1}^p)]^2 \quad (4\text{-}13)$$

where $\lambda$ is the Lagrangian multiplier that can be interpreted as a smoothness parameter. The higher $\lambda$ is, the smoother the trend and the greater the variability of the output gap. For quarterly data, Hodrick and Prescott propose λ equal to 1600.

In additional of the literatures we discussed in section 2.5.4 about estimating the Taylor rule using real time data. A number of studies highlight the importance of using real time output data in Taylor rule based exchange rate predictability (for example, Molodtsova, 2008; Molodtsova et al., 2008; Molodtsova et al., 2011; Molodtsova & Papell, 2012; Molodtsova & Papell, 2009). All these studies found stronger evidence of exchange rate predictability in models with quasi-real time data than fully revised data.

However, since real time data is only available for the U.S. among the countries we studied, we follow Molodtsova and Papell (2009) and use quasi-real time data in measuring the output gap. In this case, current vintage data is used,[30] but the trend at period t is calculated using observations 1 to $t$.

[30] Current vintage data are data available at a particular date.

### 4.4.2 Unit Root Tests

It is very likely that the exchange rate and many of the explanatory economic fundamentals are non-stationary in simple level form. Therefore, before estimating the models specified in the previous section, we proceed with testing for a unit root in the series involved. In this study, a variety of different tests such as the Augmented Dickey-Fuller test (Dickey and Fuller, 1979), KPSS (Kwiatkowski et al., 1992), Ng-Perron (2001) test and Lee and Strazicich (2003) test are used.

If the series is non-stationary and the first difference of the series is stationary, the series contains a unit root. The Augmented Dickey-Fuller (ADF) test is the most widely used test for stationary and has the unit root as the null hypothesis. Whereas the KPSS test due to Kwiatkowski et al. (1992) tests the null of a level- or trend-stationary process against the alternative of a unit root. . Kwiatkowski et al. (1992) argue that it can be of interest to test both types of hypotheses when investigating the dynamic properties of a time series.

Caner and Kilian (2001) have argued that both ADF and KPSS tests cannot distinguish very well between highly persistent stationary processes from non-stationary processes. Moreover, the power of these tests generally diminishes as more deterministic terms are added to the test regression.[31] Later, Ng and Perron (2001) proposed a method which takes into account the size distortion and power loss of the ADF and KPSS test. The Ng-Perron test has the unit root as the null hypothesis and use modified AIC and BIC in choosing the optimal lag length. They demonstrate that the choice of lag length determined by the Modified Information Criterion provide the best size and power properties of the unit root test. Moreover, they highlight the remarkable result of the Modified AIC when compared to the rest of the criteria. Therefore, in this study, the lag length in the unit root test is determined using the modified AIC criterion.

[31] Tests include a constant and trend has less power than tests with a constant only.

### 4.4.3 Unit Roots with Structural Breaks

A well-known weakness of the conventional unit root tests is that they ignore the existence of structural breaks in the variables. Ever since the seminal article of Perron (1989), researchers began to consider structural changes when testing for unit roots. Perron (1989) has shown that in the presence of structural breaks, the unit root test, which is against trend stationary alternatives, is biased to the non-rejection of the null hypothesis. His proposal is characterized by a single exogenous (known) break in the trend function. This assumption has been criticized by many studies, such as Christiano (1992). As a consequence, they conducted different methodologies to endogenously determine the break. This involves estimating a Perron (1989) type equation over all possible breaks.

Zivot and Andrews (1992) propose a modification of Perron's test in which they allow for one unknown structural break to be determined endogenously from the data. Lumsdaine and Papell (1997) extend the Zivot and Andrews's (1992) model by allowing for two structural breaks in the unit root test. One limitation of these ADF-type endogenous break unit root tests is that they tend to incorrectly select the break point (see Lee and Strazicich, 2003). To address this issue, Lee and Strazicich (2003) propose a one break LM unit root test as an alternative to Zivot Andrew test and a two break minimum Lagrange Multiplier (LM) unit root test for the Lumsdaine-Papell test. The test starts with the assumption that the null hypothesis is a unit root with up to two breaks. It not only endogenously determines the structural breaks, but the alternative hypothesis also implies the series is trend stationary (Glynn et al., 2007). The ability to permit up to two breaks in the null and two breaks in the level or slope of the alternative make this approach particularly flexible and attractive. Therefore, this study selects the Lee and Strazicich unit root test.

The Lee and Strazicich (2003) procedures for the one- and two-break LM unit root test statistic is obtained from the following regression:

$$\Delta y_t = \delta' \Delta Z_t + \phi S_{t-1} + u_t \tag{4-14}$$

where the vector of exogenous variables, $Z_t$, takes the form $[1, t, D_{jt}, DT_{jt}]$ where $j = 1{,}2$. $S_{t-1}$ is dettended value of $y_{t-1}$ and $u_t$ is the disturbance term.

We consider model A which is known as the 'crash model' and allows for time change in the intercept, $D_{jt}$. Model $C$ allows for a shift in the intercept and change in the trend slope under the alternative hypothesis.

$$D_{jt} = \begin{cases} 1 & t > T_{Bj} + 1 \\ 0 & elasewise \end{cases} \qquad DT_{jt} = \begin{cases} t - T_{Bj} & t > T_{Bj} + 1 \\ 0 & elsewise \end{cases} \tag{4-15}$$

where $T_{Bj}$ is the time period of the structural break. The LM test statistic is given by: $\tau$ = t-statistic for test where the unit root null hypothesis is that $\phi = 0$. The location of the structural break $T_B$ is determined by selecting all possible break point s for the minimum t-statistic as follows:

$$LM_\tau \lambda = inf_\lambda \tau(\lambda) \tag{4-16}$$

where $\lambda = T_B/T$. The critical value for the one- and two-break minimum LM unit root test statistics are tabulated in Lee and Strazicich (2003).

## 4.5 Data description and statistical summary

The exchange rate equation used in this study is the same as the one proposed by Molodtsova and Papell (2009) except we have also taken into account the effect of wealth in the Taylor rule. We are considering two components of the wealth effect: stock prices and house prices.

Australian, UK, Swedish and the U.S. data are used to test the Taylor rule exchange rate models in the subsequent chapters. The reason for this choice is that the U.S. was not only the country for which the Taylor rule was initially intended but also the focus of most recent research. The U.K., Australia and Sweden are of interest since they can tell us something about the suitability of using the Taylor rule in studying the exchange rate for countries that explicitly target inflation forecasts.[32] Moreover, all these three countries are relatively small,[33] have highly liquid financial markets, similar monetary policy regimes and sufficient data available for the study.

Recall the general exchange rate equation:

$$\begin{aligned}\Delta s_{t+1} = \alpha - \alpha_{u\pi}\pi_t + \alpha_{f\pi}\tilde{\pi}_t - \alpha_{uy}y_t + \alpha_{fy}\tilde{y}_t \\ - \alpha_{uw}w_t + \alpha_{fw}\tilde{w}_t + \alpha_q\tilde{q}_t - \alpha_{ui}i_{t-1} \\ + \alpha_{fi}\tilde{\iota}_{t-1} + \eta_t\end{aligned} \qquad (4\text{-}17)$$

In our empirical work, the U.S. is treated as the home country in all cases, ~ indicates variables and coefficients of countries other than the U.S. the variables' definitions are:

- $s_t$: Natural log of the U.S. nominal exchange rate, defined as the U.S. price per foreign currency ($s_t =$ dollar/foreign). So that an increase in $s_t$ is a depreciation in the dollar
- $\Delta s_{t+1} = s_{t+1} - s_t$

[32] Econometric properties of the Taylor rule relating to these countries has been studied in Österholm, P. (2005), Cobham, D. (2002), Kozicki, S. (1999) and Lee et al. (2013). These studies have shown that, in some respect, the monetary policy of these countries are characterised by Taylor rule (i.e. forecast capture policy behaviour).

[33] Kearns and Manners (2006) show that Taylor rule exchange rate model is likely to work well in a small open economy as a relatively small economy means that changes in their interest rate are unlikely to have an impact on global interest rates and therefore affect the exchange rate. This is important for isolate the impact of change in one country's interest rate on exchange rate.

- $\pi_t$: Annual inflation rate, defined as the change in the price level (measured by CPI).

  $\pi_t = \ln(CPI_t) - \ln(CPI_{t-4})$
- $y_t$: Output gap; measured as percentage deviations of actual output from a Hodrick-Prescott (1997) (HP) trend (using HP filter)
- $w_t$: stock/house price. Measured as deviation of natural log of stock price or house price from a HP filter;
- $i_{t-1}$: interest rate from the previous period
- $\tilde{q}_t$: Natural log of the real exchange rate defined as $\tilde{q}_t = s_t - (p_t - p_t^*)$, where $p_t$ is the natural log of the U.S. CPI.

The nominal exchange rates are taken to be the end of the month U.S. dollar price of a unit of foreign currency. Quarterly exchange rates have been downloaded from *DataStream*. The consumer price index (CPI) is used to measure the price level in each country; only quarterly data is available, the *International Financial Statistics* provided by the IMF are used as the data source. The inflation rate is the annual inflation rate calculated by using the CPI over the previous 4 quarters. The interest rate is the money market rate (call money rate), the data are measured in percentages, and the source is the *OECD Outlook Database*.

Real GDP data are used in output gap estimates. The data of each country are taken from the IMF international Financial Statistics Database. In order to construct the output gap, a trend are estimated based on quasi-real time. For the first vintage 1975:Q1, the trend is calculated using data from 1970:Q1 to 1974:Q4. For each subsequent vintage, we update the trend by one quarter. For example, the output gap for 1980:1 is the deviation from a trend calculated from 1970:Q1 to 1979:Q4.

The empirical research on the stock markets and exchange rate by Smith (1992), Frankel (1983a) and Lewis (1988) showed that the impact of government bonds and money on exchange rates are quite weak while equity prices have a strong impact on the exchange rate. Based on their results, we take the equity price as the measure of stock market wealth. The quarterly closing prices of the stock market indexes are used to represent the equity price in each country. The indexes we chose are the leading share market indicator in each country. The stock market indexes used are as follows: the OMX Stockholm 30 and OMX Stockholm (OMXS) for Sweden; the ASX All Ordinaries 1971 for Australian; the FTSE All Share Price Index for UK and the Standard & Poor 500 Composition Index for the US. All the indices are denominated in local currency units. The house price indices are taken from *Oxford Economics*. The series are only available quarterly.

The data set of our models is estimated using quarterly data from 1975 Q1 to 2008 Q4 for four industrialized countries. I have not updated the data to the current time since the Taylor rule has restrictions on the level of the interest rate. Once nominal interest rates approach zero, it cannot be lowered further and the Taylor rule loses power in predicting interest rate setting. The house price index data is only available from 1980Q1, so we use the data set from 1980Q1 to 2008Q4 when measuring the house price as the wealth effect.

All the data except the interest rates has been transformed to logarithmic form prior to analysis. The descriptive statistics of each country are shown in the following tables.

**Table 4-2 UK Summary Statistics**

| UK | $\Delta s_t$ | $\pi_t$ | $y_t$ | $w_t(s)$ | $w_t(h)$ | $\tilde{q}_t$ | $i_t$ | $\pi_t - \tilde{\pi}_t$ | $y_t - \tilde{y}_t$ | $w_t - \tilde{w}_t(S)$ | $w_t - \tilde{w}_t(H)$ | $i_t - \tilde{i}_t$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Mean | -0.0020 | 0.0554 | 0.0014 | -0.0007 | 0.0000 | 0.5448 | 7.8901 | 0.0121 | 0.0017 | 0.0000 | 0.0000 | 1.5363 |
| Median | 0.0001 | 0.0355 | 0.0011 | 0.0022 | -0.0058 | 0.5429 | 6.4800 | 0.0017 | 0.0019 | 0.0075 | -0.0021 | 1.3450 |
| Maximum | 0.1499 | 0.2356 | 0.0365 | 0.3119 | 0.1457 | 0.8202 | 17.1300 | 0.1556 | 0.0444 | 0.2094 | 0.1275 | 6.9000 |
| Minimum | -0.1626 | 0.0061 | -0.0397 | -0.3682 | -0.1123 | 0.1632 | 0.3100 | -0.0266 | -0.0424 | -0.3730 | -0.0743 | -6.8600 |
| Std. Dev. | 0.0515 | 0.0525 | 0.0142 | 0.1062 | 0.0435 | 0.1174 | 3.6526 | 0.0338 | 0.0164 | 0.0719 | 0.0408 | 2.5450 |
| Skewness | -0.2441 | 1.5869 | 0.0770 | -0.6472 | 1.0424 | -0.2988 | 0.5610 | 2.2832 | 0.0011 | -0.8096 | 0.6467 | -0.2014 |
| Kurtosis | 3.4479 | 4.8300 | 3.3284 | 4.6535 | 5.1522 | 3.5694 | 2.2842 | 8.6585 | 3.1107 | 8.1023 | 3.7967 | 3.7781 |
| Jarque-Bera | 2.4872 | 76.0590 | 0.7452 | 24.9882 | 43.3969 | 3.8611 | 10.0363 | 299.5962 | 0.0695 | 162.3822 | 11.1519 | 4.3498 |
| Probability | 0.2883 | 0.0000 | 0.6889 | 0.0000 | 0.0000 | 0.1451 | 0.0066 | 0.0000 | 0.9659 | 0.0000 | 0.0038 | 0.1136 |
| Observations | 136 | 136 | 136 | 136 | 116 | 136 | 136 | 136 | 136 | 136 | 116 | 136 |

*Note:* The descriptive statistics are the log form of the USD/UK exchange rate change, inflation, output gap, stock price index, house price index, real USD/UK exchange rate, interest rate, inflation difference, output gap difference, stock price difference, house price difference and interest rate difference between the US and UK, respectively. All statistics are constructed from quarterly observations running from 1975 to 2008 with definitions listed above. All differentials are measured as the US minus the foreign data.

**Table 4-3 Sweden Summary Statistics**

| Sweden | $\Delta s_t$ | $\pi_t$ | $y_t$ | $w_t(s)$ | $w_t(h)$ | $\tilde{q}_t$ | $i_t$ | $\pi_t - \tilde{\pi}_t$ | $y_t - \tilde{y}_t$ | $w_t - \tilde{w}_t(s)$ | $w_t - \tilde{w}_t(h)$ | $i_t - \tilde{i}_t$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Mean | 0.0043 | 0.0498 | 0.0007 | -0.0002 | 0.0000 | 1.8920 | 8.0796 | 0.0064 | 0.0010 | 0.0004 | 0.0000 | 1.7257 |
| Median | 0.0022 | 0.0413 | -0.0015 | -0.0180 | -0.0035 | 1.9678 | 8.2550 | 0.0027 | -0.0018 | 0.0092 | -0.0005 | 1.8650 |
| Maximum | 0.2490 | 0.1375 | 0.0491 | 0.6046 | 0.1300 | 2.4230 | 35.7800 | 0.0633 | 0.0560 | 0.4044 | 0.1318 | 32.5200 |
| Minimum | -0.1055 | -0.0112 | -0.0420 | -0.4976 | -0.0898 | 1.1252 | 1.6200 | -0.0427 | -0.0361 | -0.4953 | -0.0839 | -4.4000 |
| Std. Dev. | 0.0562 | 0.0391 | 0.0162 | 0.1999 | 0.0436 | 0.3349 | 4.5750 | 0.0259 | 0.0188 | 0.1593 | 0.0446 | 3.9932 |
| Skewness | 1.2818 | 0.4132 | 0.2540 | 0.2179 | 0.6526 | -0.7995 | 1.6046 | 0.3224 | 0.6230 | -0.0914 | 0.6087 | 3.4469 |
| Kurtosis | 6.3521 | 1.9314 | 3.8248 | 3.5877 | 3.8156 | 2.5857 | 10.9428 | 2.1512 | 3.3564 | 3.4175 | 3.6219 | 27.2233 |
| Jarque-Bera | 100.9125 | 10.3420 | 5.3173 | 3.0336 | 11.4499 | 15.4609 | 415.8643 | 6.4377 | 9.5161 | 1.1767 | 9.0322 | 3594.3290 |
| Observations | 136 | 136 | 136 | 136 | 116 | 136 | 136 | 136 | 136 | 136 | 116 | 136 |

**Table 4-4 Australia Summary Statistics**

| Australia | $\Delta s_t$ | $\pi_t$ | $y_t$ | $w_t(s)$ | $w_t(h)$ | $\tilde{q}_t$ | $i_t$ | $\pi_t - \tilde{\pi}_t$ | $y_t - \tilde{y}_t$ | $w_t - \tilde{w}_t(s)$ | $w_t - \tilde{w}_t(h)$ | $i_t - \tilde{i}_t$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Mean | -0.0051 | 0.0556 | 0.0008 | -0.0029 | 0.0000 | -0.3016 | 8.9820 | 0.0123 | 0.0011 | -0.0023 | 0.0000 | 2.6282 |
| Median | 0.0024 | 0.0457 | -0.0004 | -0.0056 | -0.0075 | -0.2749 | 7.5050 | 0.0040 | -0.0024 | -0.0067 | -0.0042 | 2.2800 |
| Maximum | 0.1144 | 0.1628 | 0.0488 | 0.4281 | 0.1361 | -0.0447 | 18.3600 | 0.0840 | 0.0484 | 0.2754 | 0.1258 | 10.5200 |
| Minimum | -0.3592 | -0.0045 | -0.0356 | -0.3826 | -0.0997 | -0.6883 | 4.2400 | -0.0344 | -0.0421 | -0.2396 | -0.1115 | -5.5500 |
| Std. Dev. | 0.0596 | 0.0378 | 0.0172 | 0.1221 | 0.0422 | 0.1589 | 4.1228 | 0.0286 | 0.0194 | 0.0969 | 0.0467 | 3.1550 |
| Skewness | -2.2882 | 0.5642 | 0.6566 | 0.4991 | 0.7792 | -0.5996 | 0.8022 | 0.7524 | 0.4066 | 0.2575 | 0.1587 | 0.2839 |
| Kurtosis | 13.0328 | 2.4558 | 3.7480 | 4.5702 | 4.2203 | 2.7014 | 2.4002 | 2.5980 | 2.6956 | 2.9113 | 3.2920 | 3.6431 |
| Jarque-Bera | 689.0707 | 8.8940 | 12.9435 | 19.6176 | 18.9364 | 8.6541 | 16.6250 | 13.7460 | 4.2716 | 1.5475 | 0.8989 | 4.1699 |
| Observations | 136 | 136 | 136 | 136 | 116 | 136 | 136 | 136 | 136 | 136 | 116 | 136 |

**Table 4-5 U.S. Summary Statistics**

| US | $\pi_t$ | $y_t$ | $w_t(s)$ | $w_t(h)$ | $i_t$ |
|---|---|---|---|---|---|
| Mean | 0.0434 | -0.0003 | -0.0007 | 0.0000 | 6.3538 |
| Median | 0.0335 | -0.0015 | -0.0004 | -0.0029 | 5.5600 |
| Maximum | 0.1355 | 0.0343 | 0.2216 | 0.0558 | 17.7800 |
| Minimum | 0.0124 | -0.0457 | -0.3279 | -0.1150 | 0.5100 |
| Std. Dev. | 0.0273 | 0.0127 | 0.0989 | 0.0224 | 3.5188 |
| Skewness | 1.5636 | -0.2275 | -0.4570 | -0.9688 | 1.0157 |
| Kurtosis | 4.9019 | 3.5774 | 3.7532 | 9.8068 | 4.2784 |
| Jarque-Bera | 75.9163 | 3.0623 | 7.9491 | 242.0905 | 32.6464 |
| Probability | 0.0000 | 0.2163 | 0.0188 | 0.0000 | 0.0000 |
| Observations | 136 | 136 | 136 | 116 | 136 |

*Note:* See notes for table 4-2.

## 4.6 Empirical results

### 4.6.1 Unit Root Tests

Normally, for variables that are expected to grow over time, we allow for a constant and a time trend under the alternative hypothesis. However, for the exchange rate differences, inflation, interest rate, output gap and real exchange rate, we expect a long-run equilibrium value which does not grow over time. Therefore, I have specified the test with a constant but no time trend in the following unit root tests for all the variables. Table 4-6 displays the ADF test results for the macroeconomic variables used in our models. In 13 out of 48 cases, we fail to reject the null of a unit root, using 95% confidence intervals.

Table 4-7 shows the results of the KPSS tests. This confirms the result from the ADF test. In 14 out of 48 cases, we reject the null of stationarity using 95% confidence intervals. But at the 90% confidence interval, there are 9 out of 48 series which exhibit a unit root.

As shown in the table, the stationarity results are country-specific. The explanatory variable $\Delta s_{t+1}$, the output gap, $y_t$ and the wealth effect, $w_t(house)$ and $w_t(stock)$ are stationary for all countries. The inflation and lagged interest rate are non-stationary for all countries. The real exchange rate, $\tilde{q}_t$ , is non-stationary for most of the countries except the UK. For all the countries, the series that are found to be non-stationary in their levels are found to be stationary in their first difference.

The last five rows of the table give the stationarity result for those models with homogeneous coefficients. Based on the results, we see strong evidence of stationarity for most of the independent variables except Sweden's inflation difference and Australia interest rate.

**Table 4-6 Unit Root Result - ADF**

| | ***UK*** | ***Sweden*** | ***Australia*** | ***US*** |
|---|---|---|---|---|
| $\Delta \boldsymbol{s_{t+1}}$ | I(0), 5% | I(0), 5% | I(0), 5% | N.A. |
| $\boldsymbol{\pi_t}$ | I(1), 5% | I(1), 5% | I(1), 5% | I(1), 5% |
| $\boldsymbol{y_t}$ | I(0), 5% | I(0), 5% | I(1), 5% | I(0), 5% |
| $\boldsymbol{\tilde{q}_t}$ | I(0), 5% | I(1), 5% | I(1), 5% | N.A. |
| $\boldsymbol{i_{t-1}}$ | I(1), 5% | I(1), 5% | I(1), 5% | I(1), 5% |
| $\boldsymbol{w_t(H)}$ | I(0), 5% | I(0), 5% | I(0), 5% | I(0), 5% |
| $\boldsymbol{w_t(S)}$ | I(0), 5% | I(0), 5% | I(0), 5% | I(0), 5% |
| $\boldsymbol{\pi_t - \tilde{\pi}_t}$ | I(0), 5% | I(1), 5% | I(0), 5% | N.A. |
| $\boldsymbol{y_t - \tilde{y}_t}$ | I(0), 5% | I(0), 5% | I(0), 5% | N.A. |
| $\boldsymbol{i_{t-1} - \tilde{i}_{t-1}}$ | I(0), 5% | I(0), 5% | I(1), 5% | N.A. |
| $\boldsymbol{w_t - \tilde{w}_t(H)}$ | I(0), 5% | I(0), 5% | I(0), 5% | N.A |
| $\boldsymbol{w_t - \tilde{w}_t}$ | I(0), 5% | I(0), 5% | I(0), 5% | N.A. |

*Note:* the null hypothesis of the ADF test is that the variable contains a unit root. So I(0), 5% mean the ADF test reject a unit root (at 5%); $y_t$ is adjusted using HP filter.

**Table 4-7 Unit Root Result - KPSS**

| | *UK* | *Sweden* | *Australia* | *US* |
|---|---|---|---|---|
| $\Delta s_{t+1}$ | I(0), 5% | I(0), 5% | I(0), 5% | N.A. |
| $\pi_t$ | I(1), 5% | I(1), 5% | I(1), 5% | I(1), 5% |
| $y_t$ | I(0), 5% | I(0), 5% | I(1), 5% | I(0), 5% |
| $\tilde{q}_t$ | I(0), 5% | I(1), 5% | I(1), 5% | N.A. |
| $i_{t-1}$ | I(1), 5% | I(1), 5% | I(1), 5% | I(1), 5% |
| $w_t(house)$ | I(0), 5% | I(0), 5% | I(0), 5% | I(0), 5% |
| $w_t(stock)$ | I(0), 5% | I(0), 5% | I(0), 5% | I(0), 5% |
| $\pi_t - \tilde{\pi}_t$ | I(1), 5% | I(1), 5% | I(0), 5% | N.A. |
| $y_t - \tilde{y}_t$ | I(0), 5% | I(0), 5% | I(0), 5% | N.A. |
| $i_{t-1} - \tilde{i}_{t-1}$ | I(0), 5% | I(0), 5% | I(1), 5% | N.A. |
| $w_t - \tilde{w}_t(S)$ | I(0), 5% | I(0), 5% | I(0), 5% | N.A |
| $w_t - \tilde{w}_t(H)$ | I(0), 5% | I(0), 5% | I(0), 5% | N.A. |

*Note:* the null hypothesis of the KPSS test is that the variable is trend stationary. So I(0), 5% means the KPSS cannot reject the stationary at 5% level; $y_t$ is adjusted using HP filter.

**Table 4-8 Unit Root Result - Perron-Ng**

| | *UK* | *Sweden* | *Australia* | *US* |
|---|---|---|---|---|
| $\Delta s_{t+1}$ | I(0), 5% | I(0), 5% | I(0), 5% | N.A. |
| $\pi_t$ | I(1), 5% | I(1), 5% | I(0), 5% | I(0), 5% |
| $y_t$ | I(0), 5% | I(0), 5% | I(1), 5% | I(0), 5% |
| $\tilde{q}_t$ | I(0), 5% | I(1), 5% | I(0), 5% | N.A. |
| $i_{t-1}$ | I(1), 5% | I(0), 5% | I(0), 5% | I(1), 5% |
| $w_t(house)$ | I(0), 5% | I(0), 5% | I(0), 5% | I(0), 5% |
| $w_t(stock)$ | I(0), 5% | I(0), 5% | I(0), 5% | I(0), 5% |
| $\pi_t - \tilde{\pi}_t$ | I(0), 5% | I(0), 5% | I(0), 5% | N.A. |
| $y_t - \tilde{y}_t$ | I(0), 5% | I(0), 5% | I(0), 5% | N.A. |
| $i_{t-1} - \tilde{i}_{t-1}$ | I(0), 5% | I(0), 5% | I(0), 5% | N.A. |
| $w_t - \tilde{w}_t(S)$ | I(0), 5% | I(0), 5% | I(0), 5% | N.A |
| $w_t - \tilde{w}_t(H)$ | I(0), 5% | I(0), 5% | I(0), 5% | N.A. |

*Note:* the null hypothesis of the Perron-Ng test is that the variable contains a unit root. So I(0), 5% mean the Perron-Ng test reject a unit root (at 5%); $y_t$ is adjusted using HP filter.

Table 4-8 show Perron-Ng test results. It can be seen from the table that the tests provide better results than the above two. However, for individual series, the unit root null cannot by reject for most of the individual series, i.e. 6 out of 48 series are still I(1). Failure to incorporate structural changes in testing the unit root of these series may be the possible reason for bias in finding the result of non-stationarity. However, there is an improvement in the result with homogeneous coefficients. The Perron-Ng tests shows all variables are stationary.

The limitation of the above test is that it does not account for potential structural breaks in the series. To address this issue, we first allow for one break in the LS unit root test. Table 4-9 and Table 4-10 present the results for the Lee and Strazicich test with one structural break.

Beginning with Table 4-11, more variables become stationary after the application of the Lee-Strazicich test. In the case of heterogeneous coefficients, the LS unit root test with one break in the intercept reject the unit root null for 22 of the 26 variables at 5 or 10 percent. The UK output gap is I(1) here but stationary under all of conventional unit root tests. Take the conventional test as test for unit root with no structural break, we conclude it is stationary with no structural break. In the case of homogeneous coefficients, we rejects the unit root null for all variables at the 5% significance level or better.

In allowing for a second structural break,[34] we find variables become stationary in the remaining series at either 5 or 10 percent. These results are presented in Table 4-11 to Table 4-14. The only series for which the unit root null is not rejected are the UK output gap and Sweden's real exchange rate. Since the UK output gap is I(0) in

[34] Note that allowing for additional breaks does not necessarily produce more rejections of the unit root null. This is because the critical values will rise as more breaks are added which causes a loss of power if too many break points are included. Therefore, we will consider the additional rejection as evidence in favour of the two break model.

all conventional unit root tests, we conclude that the UK output gap is stationary with zero structural breaks.

In total, we have used four different tests to verify the stationarity of the variables. If we conclude those variables which are I (0) under conventional unit root tests but are I (1) under the Lee Strazicich test, as stationary with no structural break and consider those I (0) variables in either one of the conventional or Lee Strazicich as stationary, then we can conclude that apart from the Swedish real exchange rate, all variables are stationary.

**Table 4-9 One Break Lee Strazicich Test**

| | | ***UK*** | | ***Sweden*** | | ***Australian*** | |
|---|---|---|---|---|---|---|---|
| ***variables*** | ***model*** | ***t-statistics*** | ***break date*** | ***t-statistics*** | ***break date*** | ***t-statistics*** | ***break date*** |
| $\Delta s_{t+1}$ | A | -4.0101* | 1980:01 | -6.6866* | 2001:01 | -6.9187* | 1985:01 |
| $\pi_t$ | A | -5.1396* | 1985:02 | -6.2031* | 1994:03 | -5.8468* | 2000:01 |
| $y_t$ | A | -4.1115 | 1978:04 | -6.8584* | 2005:02 | -5.1151* | 1985:02 |
| $\tilde{q}_t$ | A | -4.0772* | 1986:03 | -2.9814 | 1984:04 | -3.274** | 1985:02 |
| $i_{t-1}$ | A | -4.5221* | 1992:03 | -7.1603* | 1993:02 | -3.5384 | 1991:01 |
| $w_t(house)$ | A | -4.8287* | 1987:02 | -4.8584* | 1988:01 | -3.9666 | 1988:01 |
| $w_t(stock)$ | A | -5.5372* | 2002:04 | -5.4708* | 1982:01 | -5.6244* | 2005:03 |
| $\pi_t - \tilde{\pi}_t$ | A | -7.5086* | 1991:02 | -5.8380* | 1993:01 | -3.7506 | 2001:02 |
| $y_t - \tilde{y}_t$ | A | -5.3955* | 1983:03 | -5.8464* | 1992:02 | -5.3360* | 1982:01 |
| $i_{t-1} - \tilde{i}_{t-1}$ | A | -4.8120* | 1992:03 | -4.2090* | 1993:02 | -3.0798 | 1990:01 |
| $w_t - \tilde{w}_t(H)$ | A | -5.0372* | 2004:01 | -4.8003* | 1992:01 | 5.7839* | 2005:01 |
| $w_t - \tilde{w}_t(S)$ | A | -6.9614* | 1979:02 | -5.6860* | 1982:01 | -5.0880* | 1986:02 |

*Notes:* the critical value are listed in Appendix I; * ,** denote the unit root is rejected if allowed for 1 structural break at 5% and 10% significant level;

**Table 4-10 One Break Lee Strazicich Test (continued)**

| *U.S.* | | | |
|---|---|---|---|
| ***variables*** | ***model*** | ***t-statistics*** | ***break date*** |
| $\boldsymbol{\pi_t}$ | A | -4.7665* | 1982:02 |
| $\boldsymbol{y_t}$ | A | -5.2147* | 2004:03 |
| $\boldsymbol{i_{t-1}}$ | A | -5.0039* | 1980:02 |
| $\boldsymbol{w_t}(\boldsymbol{house})$ | A | -6.1388* | 2004:02 |
| $\boldsymbol{w_t}(\boldsymbol{stock})$ | A | -4.9267* | 1982:02 |

*Notes:* the critical values are listed in Appendix I. * ,** denote the unit root is rejected if allowed for 1 structural break at 5% and 10% significant level;

**Table 4-11 Two break Lee Strazicich Test -- UK**

| *LS for UK with two structural break* | | | | |
|---|---|---|---|---|
| ***variables*** | ***model*** | ***t-statistics*** | ***break date 1*** | ***break date 2*** |
| $\Delta \boldsymbol{s_{t+1}}$ | A | -4.3267 | 1987:01 | 1996:04 |
| $\boldsymbol{\pi_t}$ | A | -6.2226* | 1988:04 | 1998:03 |
| $\boldsymbol{y_t}$ | A | -4.7198 | 1981:02 | 1987:01 |
| $\boldsymbol{\tilde{q}_t}$ | A | -4.3795 | 1984:03 | 1987:04 |
| $\boldsymbol{i_{t-1}}$ | A | -6.0390* | 1979:01 | 1993:01 |
| $\boldsymbol{w_t}(\boldsymbol{house})$ | A | -5.3467** | 1990:02 | 2003:02 |
| $\boldsymbol{w_t}(\boldsymbol{stock})$ | A | -6.1856* | 2001:04 | 2005:03 |
| $\boldsymbol{\pi_t - \tilde{\pi}_t}$ | A | -8.1222* | 1982:02 | 1998:04 |
| $\boldsymbol{y_t - \tilde{y}_t}$ | A | -6.1054* | 1983:03 | 1987:02 |
| $\boldsymbol{i_{t-1} - \tilde{i}_{t-1}}$ | A | -6.0934* | 1984:03 | 1993:01 |
| $\boldsymbol{w_t - \tilde{w}_t}(\boldsymbol{H})$ | A | -6.5291* | 1988:01 | 1992:01 |
| $\boldsymbol{w_t - \tilde{w}_t}(\boldsymbol{S})$ | A | -7.1051* | 1979:02 | 1993:02 |

*Notes:* the critical value are listed in Appendix I; * ,** denote the unit root is rejected if allowed for 2 structural breaks at 5% and 10% significant level;

**Table 4-12 Two break Lee Strazicich Test -- Sweden**

| *LS for Sweden with two structural break* | | | | |
|---|---|---|---|---|
| *variables* | *model* | *t-statistics* | *break date 1* | *break date 2* |
| $\Delta s_{t+1}$ | A | -8.0072* | 1984:04 | 1992:04 |
| $\pi_t$ | A | -6.9902* | 1987:01 | 1993:01 |
| $y_t$ | A | -7.1571* | 1992:03 | 2004:03 |
| $\tilde{q}_t$ | A | -3.1620 | 1984:04 | 2002:02 |
| $i_{t-1}$ | A | -8.0862* | 1979:02 | 1993:02 |
| $w_t(house)$ | A | -5.3666** | 1988:01 | 1993:02 |
| $w_t(stock)$ | A | -6.0982* | 2002:01 | 2005:02 |
| $\pi_t - \tilde{\pi}_t$ | A | -6.3519* | 1980:01 | 1993:01 |
| $y_t - \tilde{y}_t$ | A | -6.3489* | 1987:04 | 1992:01 |
| $i_{t-1} - \tilde{i}_{t-1}$ | A | -7.0119* | 1978:04 | 1993:02 |
| $w_t - \tilde{w}_t(H)$ | A | -5.5675** | 1988:03 | 1994:02 |
| $w_t - \tilde{w}_t(S)$ | A | -6.0231* | 1982:01 | 1986:94 |

*Notes:* the critical value are listed in Appendix I; * ,** denote the unit root is rejected if allowed for 2 structural breaks at 5% and 10% significant level;

**Table 4-13 Two break Lee Strazicich Test -- Australia**

| *LS for Australian with two structural break* | | | | |
|---|---|---|---|---|
| *variables* | *model* | *t-statistics* | *break date1* | *break date 2* |
| $\Delta s_{t+1}$ | A | -7.3635* | 2002:01 | 2005:03 |
| $\pi_t$ | A | -7.1707* | 1981:01 | 1991:01 |
| $y_t$ | A | -5.7343* | 1982:02 | 1988:01 |
| $\tilde{q}_t$ | A | -3.5603** | 1985:02 | 1989:01 |
| $i_{t-1}$ | A | -6.2278* | 1989:02 | 1994:02 |
| $w_t(house)$ | C | -6.1770* | 1985:01 | 1988:01 |
| $w_t(stock)$ | C | -6.2226* | 1988:02 | 2005:03 |
| $\pi_t - \tilde{\pi}_t$ | A | -6.9563* | 1981:02 | 1990:02 |
| $y_t - \tilde{y}_t$ | A | -5.6373* | 1982:04 | 1989:04 |
| $i_{t-1} - \tilde{i}_{t-1}$ | A | -5.6332** | 1983:04 | 1992:04 |
| $w_t - \tilde{w}_t(H)$ | A | -6.5323* | 1985:02 | 1989:02 |
| $w_t - \tilde{w}_t(S)$ | A | -5.3407** | 1986:02 | 1991:01 |

*Notes:* the critical value are listed in Appendix I; * ,** denote the unit root is rejected if allowed for 2 structural breaks at 5% and 10% significant level;

**Table 4-14 Two break Lee Strazicich Test – U.S.**

| *LS for US with two structural break* | | | | |
|---|---|---|---|---|
| ***variables*** | ***model*** | ***t-statistics*** | ***break date1*** | ***break date 2*** |
| $\boldsymbol{\pi_t}$ | A | 5.5874** | 1982:04 | 1979:01 |
| $\boldsymbol{y_t}$ | A | -5.6044** | 2001:03 | 2005:03 |
| $\boldsymbol{i_{t-1}}$ | A | -5.9757* | 1980:02 | 1984:03 |
| $\boldsymbol{w_t}(\boldsymbol{house})$ | A | -6.5717* | 2001:04 | 2005:02 |
| $\boldsymbol{w_t}(\boldsymbol{stock})$ | A | -5.8091* | 2001:04 | 2005:03 |

*Note:* the critical value are listed in Appendix I; * ,** denote the unit root is rejected if allowed for 2 structural breaks at 5% and 10% significant level;

Recalling that unless all the variables in the regression are stationary, its estimation in levels might be misleading and incorrect and leading to a spurious regression. From the previous result, that the Swedish real exchange rate is still non-stationary after taking into account two structural breaks. In order to run our regression, we try an alternative model specification for Sweden by replacing the Swedish real exchange rate by the differenced real exchange rate.

**Table 4-15 Unit root test for Sweden Real Exchange Rate Difference**

| ***Sweden real exchange rate difference*** | | |
|---|---|---|
| ***ADF*** | -8.615202* | |
| ***KPSS*** | 0.228660* | |
| ***Perro-Ng*** | I(0) | |
| ***Lee-Strazicich with one break*** | -3.5113** | 1993:03 |
| ***Lee-Strazicich with two break*** | -3.7491** | 1985:01, 1993:03 |

*Note:* I(0) mean the Perro-Ng test reject a unit root at 5%. *, ** denote the unit root is rejected at 5% and 10% significant level; the critical value for Lee-Strazicich tests are listed in Appendix I;

The results from the four unit root tests on the modified new variable are presented in Table 4-15. The results show strong evidence of stationarity. In all conventional unit root tests, so we can reject the unit root null even at the 1% level. The Lee

Strazicich result shows it is stationary at 10%. Therefore, we conclude the Swedish real exchange rate difference is stationary with no structure break. And we will use this instead of the real exchange rate in our regression analysis for Sweden.

### 4.6.2 The Cause of the Breaks

Another interesting point to discuss is the break dates themselves. The reason we are using unit root tests with structural breaks is that the conventional unit root test assumes no structural break under the unit root null. Due to this, it often leads to a false failure to rejection of the unit root null hypothesis. Therefore, we only consider breaks if a variable is concluded to be non-stationary in all of the conventional tests. Table 4-16 lists the break points we considered for each of the countries we studied measured at the 95% confidence interval. Note that the break dates for different countries varies considerably.

Most of the break dates can be explained by changes in the exchange rate regime or monetary policies in these countries. For example, For the UK, the first break corresponds with the abandoning of the £M3 target in October 1985. This is part of the MTFS the government announced in March 1980. It was originally aiming to reduce inflation and create conditions for sustainable economic growth. However, with the overshooting of the £M3 target, the UK economy went into a deep recession. The authorities had then successively downgraded its importance and by October 1985, the plan was finally abandoned. The second breaks can be viewed as a result of the UK leaving the ERM.[35]

[35] The European exchange rate mechanism; Within the ERM, Germany was dominant and other countries followed German interest rate policy.

**Table 4-16 Break description**

| ***country*** | ***break point*** | ***Event*** |
|---|---|---|
| ***UK*** | 1985:02 | *Due to the overshooting of the £M3 target, inflation falling at a heavy cost of a deep recession. Therefore, in October 1985, authorities abandon the £M3 target. Inflation rise* |
| | 1992:03 | *UK left ERM, interest rate fall* |
| ***Sweden*** | 1994:03 | *Economic recovery* |
| ***Australia*** | 1985:02 | *Adopt independent floating exchange rate* |
| ***US*** | 1980:02 | *The Treasury Department and the Federal Reserve announced a package of measures to strengthen the Dollar. There would be increased intervention in the foreign exchange markets, in cooperation with the central banks of the Federal Republic of Germany, Japan, and Switzerland. (IMF 1979, p.435)* |

*Notes:* The table lists all the significant break points for each of the countries studied. Each break point is reflects either changes in exchange rate regime or monetary policy. A more detailed description can be found in Chapter 3.

In this study, I have taken 5% significance levels in measuring break points for the UK, Sweden and Australia.

### 4.6.3 The OLS result

To a large extent, the previous studies on the Taylor rule exchange rate model did not properly address the time series properties of the variables and the properties of the estimated models, there are also a few papers that completely ignored model estimation.[36] This is especially important since the above results give evidence that the variables in the Taylor rule exchange rate model contain unit roots as well as some structural breaks for same countries and sub-samples.[37]

If we are using a Taylor rule to evaluate central bank behaviour or to model the exchange rate, the econometric properties of the model should first be scrutinised. Having done this, we are now in a position to estimate the model. Table 4-17 to Table 4-28 present the basic OLS results of equation (4-17). With a choice between symmetric and asymmetric, homogeneous and heterogeneous, with and without smoothing, we estimate eight models with two measures of the wealth effect for each country: stock price and house. Furthermore, models without the wealth effect are re-estimated with quarterly data and results are listed in the Appendix II. The reason for including these original Molodtsova and Papell (2009) models is to see whether or not variations in wealth have an impact on the exchange rate. Therefore, sixteen specifications of the Taylor rule exchange rate models with wealth factors are estimated with results listed in Table 4-17 to Table 4-28. Eight specifications of Molodtsova and Papell (2009) Taylor rule models are estimated with result listed in the Appendix II. In total, 24 different specifications are studied in this chapter.

Given the various assumptions, we have discussed different predictions regarding the signs in the exchange rate models in section 4.3.2. Our results give mixed coefficient signs. The coefficient on the real exchange rate is negative, as predicted with the UIRP assumption. Other variables have signs which vary according to different models. Neither the Dornbusch (1976) nor the Molodtsova and Papell (2009) sign predictions hold in our case. This confirms the viewpoint that it is not always possible to define the signs in the equations as discussed in Molodtsova, et al. (2008).

[36] See for example, Molodtsova and Papell (2009), Galimberti, J.K and M.L. Moura (2012). Molodtsova et al.(2008), Jian, W. and J. Wu (2009);

[37] See for example, GLORIA, M. C. (2010).

Models with different measures of the wealth effects are estimated over different time periods: stock price models are estimated using 1975-2008 data. House price data are only available since 1980, so all models with house prices as the measure of wealth use 1980-2008 data. Therefore, we will illustrate results of these models with different wealth effect measurements separately for the four countries we have studied.

Furthermore, dummy variables are included in the models to capture the effect of structural breaks as listed in Table 4-16. Intercept dummies are constructed for all series containing breaks in the intercept (model A).[38] All the Taylor rule exchange rate models are estimated by Ordinary Least Square with Newey-West corrected standard-errors.

### *Exchange Rate Models without Wealth Effect vs. Exchange Rate with Wealth effect*

The Taylor rule exchange rate models derived by Molodtsova and Papell (2009) assumes changes in the exchange rate depend on the output gap, difference between inflation rates, the lagged interest rate and real exchange rate of the foreign country. In total, 16 specifications are derived based on monthly data.[39] In this chapter, I estimate their models and produce the results on quarterly data with the assumption of the non-constant ignored. [40] Results are listed in Appendix III.

[38] This is defined in section 4.6.1.

[39] The 16 specifications are modes with: domestic country target /not target the exchange rate(i.e. asymmetric/symmetric), interest rate adjust /not adjust to target level within period (i.e. smoothing/non smoothing), constant/non-constant term and equal/ not equal coefficient in Taylor rule(i.e. homogeneous/heterogeneous).

[40] Model estimation has been ignored in Molodtsova and Papell's (2009) paper.

Comparing the in sample performance of the models without wealth effects to models with wealth effects, we found that including wealth effects improves the performance of the classical models developed by Molodtsova and Papell (2009). This is reflected by both higher adjusted R-square statistics of the models and *t*-statistics of each individual variable.

### ***Exchange rate models with stock prices***

We will first illustrate results for the US-UK exchange rate. The results are listed in the Table 4-17 to Table 4-18. Based on the break date results, three structural dummy variables are specified in the exchange rate equation to allow for intercept.[41]

Based on the number of significant variables in a regression, the best model for the US-UK exchange rate with stock prices included is the asymmetric model with smoothing and heterogeneous coefficients (see Model 1). The coefficients on most of the variables have the signs confirming the assumptions in Molodtsova and Papell (2009) except for inflation and the real exchange rate. Apart from the US output gap, all variables are significantly different from zero at the 5% significance level. The stock price has a significant impact on the exchange rate. This confirms the result of, Ajayi and Mougoue (2004) although they have used different methods and models in studying the relationship between stock prices and exchange rates. The result of the adjusted R-square statistic confirms the results of the above in showing that the asymmetric model with smoothing and heterogeneous coefficient is the best among the eight specifications of Taylor rule exchange rate models, we note that models assume the UK targets the exchange rate (i.e. asymmetric) are better than others in explaining exchange rate movements. Model 1, Model 3, Model 9 and Model 11 in Table 4-17 and Table 4-18 present the results for the asymmetric Taylor rule models, the adjusted R-square statistics indicate the asymmetric models, with the inclusion

[41] The structural dummy variable for each break date takes the value of 1 for the observations between the break date in question and the subsequent break date, and 0 otherwise.

of the real exchange rate, appear more relevant to explaining exchange rate movements. This pattern obeys the British monetary policy setting during this period as Davradakis and Taylor (2006) also found a significant asymmetry in their study about monetary policy. Moreover, in the case where the real exchange rate is not included (see Model 5 and Model 13), the dummy variables becomes jointly insignificant. Furthermore, the OLS estimate for the US-UK also implies the models with interest rate smoothing perform better than models without smoothing.

The results for the US-Sweden and US-Australian exchange rates can be found in Table 4-19 to Table 4-22. For the US-Sweden exchange rate, two dummy variables are included in the regression to account for the intercept in Sweden's inflation rate and US interest rate. The real exchange rate difference is used instead of the real exchange rate, as explained earlier regarding the issue of stationarity. The reason is illustrated as above in section 4.6.1. The *t*-statistics show that the stock price is not a significant factor for determining the exchange rate in Sweden.

The US-Australia results are listed in the last panel. At the 5% significance level, all the variables have become stationary apart from US interest rate and Australia output gap. Thus, the regressions for the US-Australia are run with two dummy variables. As indicated by the *t*-statistics, the stock price is an important variable in explaining exchange rate changes. The real exchange rate is significant in all the models suggesting that the asymmetric models (i.e. models with real exchange rate) are better than the symmetric models. This confirms De Bouwer and Gilbert (2005) findings on monetary policy, where the Reserve Bank of Australia seems to consider the exchange rate in its policy setting. The coefficients on the lagged interest rates are insignificant in our models, which means the inclusion of the smoothing effect does not change the result substantially. This is also confirmed when we compare the adjusted R-square statistics of the models with and without lagged interest rates. Furthermore, judging by the adjusted R-squared statistic, models with restricted coefficients have better explanatory power than models with unrestricted coefficients.

Based on the above, we found that the asymmetric models with no smoothing and homogenous coefficients are better than the others in explaining the Australia/US exchange rate movements. However, even in this model, the estimate of the coefficient is not very supportive of the Taylor rule as a reasonable description of the Australia/US exchange rates. Almost all the coefficients are not significantly different from zero. This is not a surprise as similar results have been found in previous studies for Australia's policy reaction function.[42] Nevertheless, the stock price remains significant at the 5% level in all models. The highest adjusted R-square statistic is 6.1% (see Model 11), with most of the variation in the dependent variable explained by the real exchange rate and stock price. This suggests that without the wealth effect, the Taylor rule exchange rate is mis-specified.

**Table 4-17 Estimation of Taylor rule exchange rate models for the UK - heterogeneous coefficients with stock price**

| | *Model 1* | *Model 5* | *Model 9* | *Model 13* |
|---|---|---|---|---|
| $\boldsymbol{c}$ | 0.124* | 0.041 | 0.036 | 0.007 |
| $\boldsymbol{\pi_t}$ | 1.268* | 0.216 | 1.185* | -0.127 |
| $\boldsymbol{\tilde{\pi}_t}$ | -0.643* | -0.293 | -0.254 | -0.092 |
| $\boldsymbol{y_t}$ | -0.302 | 0.078 | -0.701 | -0.106 |
| $\boldsymbol{\tilde{y}_t}$ | 1.264* | 0.625 | 0.841** | 0.478 |
| $\boldsymbol{\tilde{q}_t}$ | -0.207* | - | -0.220* | - |
| $\boldsymbol{i_{t-1}}$ | -0.008* | -0.005* | - | - |
| $\boldsymbol{\tilde{i}_{t-1}}$ | 0.003* | 0.001 | - | - |
| $\boldsymbol{w_t}$ | -0.183* | -0.209* | -0.129* | -0.185* |
| $\boldsymbol{\tilde{w}_t}$ | 0.164* | 0.180* | 0.136* | 0.156* |
| ***Dummies*** | 2.391* | 1.449 | 3.672* | 1.302 |
| ***R-squared*** | 0.262 | 0.144 | 0.204 | 0.087 |
| ***Adj. R-squared*** | 0.168 | 0.044 | 0.146 | 0.029 |
| $\boldsymbol{\hat{\sigma}}$ | 0.047 | 0.051 | 0.048 | 0.051 |
| ***Log likelihood*** | 227.327 | 217.459 | 224.255 | 215.058 |
| ***F-statistic*** | 1.758 | 0.629 | 2.787* | 0.245 |

*Note*: table show coefficient of the variable over the entire sample period. Models are estimated by OLS where standard errors have been Newey-West corrected. Dummies is the *F*-statistics for jointly significance of dummy variable. $\hat{\sigma}$ is the standard error of the regression. *F*-statistics is the Wald test for coefficient equality restriction discussed later in this section. *and **means significance at 5% and 1% significant level, respectively.

[42] For example, Leu and Sheen (2006)

**Table 4-18 Estimation of Taylor rule exchange rate models for the UK - homogeneous coefficients with stock price**

| | *Model 3* | *Model 7* | *Model 11* | *Model 15* |
|---|---|---|---|---|
| $c$ | 0.056* | -0.006 | 0.061* | -0.001 |
| $\tilde{\pi}_t - \pi_t$ | -0.286 | -0.146 | -0.32** | -0.177 |
| $\tilde{y}_t - y_t$ | 0.598 | 0.258 | 0.691 | 0.348 |
| $\tilde{q}_t$ | -0.112* | - | -0.111* | - |
| $\tilde{i}_{t-1} - i_{t-1}$ | 0.003** | 0.003 | - | - |
| $\tilde{w}_t - w_t$ | 0.186* | 0.198* | 0.147* | 0.159* |
| ***R-squared*** | 0.142 | 0.088 | 0.112 | 0.058 |
| ***Adj. R-squared*** | 0.109 | 0.051 | 0.084 | 0.037 |
| $\hat{\sigma}$ | 0.0489 | 0.050 | 0.049 | 0.051 |
| ***Log likelihood*** | 217.252 | 213.136 | 216.866 | 212.933 |

*Note*: see notes on table 4-17.

**Table 4-19 Estimation of Taylor rule exchange rate models for the Sweden - heterogeneous coefficients with stock price**

| | *Model 1* | *Model 5* | *Model 9* | *Model 13* |
|---|---|---|---|---|
| $c$ | -0.152* | -0.15* | -0.024 | -0.028 |
| $\pi_t$ | 0.895** | 0.897** | 0.347 | 0.300 |
| $\tilde{\pi}_t$ | 0.268 | 0.248 | 0.142 | 0.249 |
| $y_t$ | -0.410 | -0.408 | -0.129 | -0.113 |
| $\tilde{y}_t$ | -0.812* | -0.790* | -0.438 | -0.538 |
| $\tilde{q}_t$ | -0.019 | - | 0.110 | - |
| $i_{t-1}$ | -0.001 | -0.001 | - | - |
| $\tilde{i}_{t-1}$ | 0.008* | 0.008* | - | - |
| $w_t$ | 0.062 | 0.061 | 0.071 | 0.082 |
| $\tilde{w}_t$ | 0.048 | 0.047 | -0.028 | -0.028 |
| ***Dummies*** | 6.242* | 6.761* | 0.510 | 0.658 |
| ***R-squared*** | 0.221 | 0.221 | 0.077 | 0.067 |
| ***Adj. R-squared*** | 0.137 | 0.144 | 0.010 | 0.008 |
| $\hat{\sigma}$ | 0.052 | 0.052 | 0.056 | 0.056 |
| ***Log likelihood*** | 215.036 | 215.012 | 203.584 | 202.859 |
| ***F-statistic*** | 0.952 | 1.287 | 0.732 | 1.254 |

*Note*: see notes on table 4-17.

**Table 4-20 Estimation of Taylor rule exchange rate models for the Sweden - homogeneous coefficients with stock price**

| | *Model 3* | *Model 7* | *Model 11* | *Model 15* |
|---|---|---|---|---|
| $c$ | 0.002 | 0.002 | 0.005 | 0.005 |
| $\tilde{\pi}_t - \pi_t$ | -0.182 | -0.098 | -0.028 | 0.066 |
| $\tilde{y}_t - y_t$ | -0.195 | -0.286 | -0.230 | -0.320 |
| $\tilde{q}_t$ | 0.149 | - | 0.153** | - |
| $\tilde{i}_{t-1} - i_{t-1}$ | 0.002 | 0.002 | - | - |
| $\tilde{w}_t - w_t$ | -0.023 | -0.022 | -0.045 | -0.045 |
| *R-squared* | 0.062 | 0.043 | 0.044 | 0.023 |
| *Adj. R-squared* | 0.026 | 0.013 | 0.015 | 0.001 |
| $\hat{\sigma}$ | 0.055 | 0.056 | 0.056 | 0.056 |
| *Log likelihood* | 200.576 | 199.204 | 201.249 | 199.797 |

*Note*: see notes on table 4-17.

**Table 4-21 Estimation of Taylor rule exchange rate models for the Australia - heterogeneous coefficients with stock price**

| | *Model 1* | *Model 5* | *Model 9* | *Model 13* |
|---|---|---|---|---|
| $c$ | -0.024 | 0.012 | -0.030 | 0.002 |
| $\pi_t$ | 0.022 | -0.371 | -0.113 | -0.40 |
| $\tilde{\pi}_t$ | 0.298 | 0.344 | 0.164 | 0.194 |
| $y_t$ | 0.439 | 0.552 | 0.172 | 0.320 |
| $\tilde{y}_t$ | -0.279 | -0.422 | -0.268 | -0.401 |
| $\tilde{q}_t$ | -0.07** | - | -0.071** | - |
| $i_{t-1}$ | -0.002 | -0.001 | - | - |
| $\tilde{i}_{t-1}$ | -0.000 | -0.001 | - | - |
| $w_t$ | -0.183* | -0.202* | -0.181* | -0.19* |
| $\tilde{w}_t$ | 0.130* | 0.145* | 0.131* | 0.143* |
| *Dummies* | 19.235* | 19.237* | 13.350* | 22.407* |
| *R-squared* | 0.112 | 0.088 | 0.096 | 0.076 |
| *Adj. R-squared* | 0.048 | 0.030 | 0.047 | 0.032 |
| $\hat{\sigma}$ | 0.0586 | 0.059 | 0.058 | 0.059 |
| *Log likelihood* | 195.283 | 193.488 | 196.059 | 194.523 |
| *F-statistic* | 1.073 | 1.998** | 0.353 | 1.735 |

*Note*: see notes on table 4-17.

**Table 4-22 Estimation of Taylor rule exchange rate models for the Australia - homogeneous coefficients with stock price**

| | *Model 3* | *Model 7* | *Model 11* | *Model 15* |
|---|---|---|---|---|
| $c$ | -0.027* | -0.007 | -0.027* | -0.007 |
| $\tilde{\pi}_t - \pi_t$ | 0.149 | 0.176 | 0.157 | 0.202 |
| $\tilde{y}_t - y_t$ | -0.180 | -0.333 | -0.176 | -0.330 |
| $\tilde{q}_t$ | -0.068* | - | -0.067* | - |
| $\tilde{i}_{t-1} - i_{t-1}$ | 0.001 | 0.000 | - | - |
| $\tilde{w}_t - w_t$ | 0.144* | 0.145* | 0.144* | 0.145* |
| ***R-squared*** | 0.090 | 0.059 | 0.089 | 0.058 |
| ***Adj. R-squared*** | 0.055 | 0.030 | 0.061 | 0.037 |
| $\hat{\sigma}$ | 0.058 | 0.059 | 0.058 | 0.059 |
| ***Log likelihood*** | 193.664 | 191.421 | 195.543 | 193.320 |

*Note*: see notes on table 4-17.

### *Exchange rate models with house prices*

The results of the models with house prices are shown in Table 4-23 to Table 4-28. For the US-UK exchange rate, ranking it by the number of significant variables, the best model is the asymmetric model with smoothing and heterogeneous coefficients (see Model 2). In this model, most coefficients are significant except the US inflation rate, US output gap and UK interest rate. Both UK and US house prices are significant in explaining changes in the exchange rate. The adjusted R-square result confirms the conclusion from the *t*-statistics and shows that 35.3% of the variation in exchange rates is explained. The significance of the house prices disappears in the other exchange rate models. For example, there is no significance of the house prices in models with homogenous coefficients (Model 4, 8, 12 and 16). In the symmetric model with smoothing and the heterogeneous coefficients (Model 6), the US house prices are insignificant. The adjusted R-square statistic shows models with heterogeneous coefficients to be better than homogenous coefficients. This is largely due to the joint significance of the dummy variables. Moreover, *t*-statistics show that the real exchange rate is highly significant in all models. This is also the case when we study models with stock prices.

For the US-Sweden exchange rate, the *t*-statistics show that the house prices are relevant factors in explaining changes in the exchange rate. The coefficient sign on the house price and lagged interest rate are the same as the assumed signs in Molodtsova and Papell (2009), while other variables have signs which vary across different models. Judging by the adjusted R-square, the best performing models are those with smoothing and heterogeneous coefficients (see Model 2 and Model 6). Within these two models, we find most of the coefficients on the variables are significantly different from zero. Moreover, the symmetric model (i.e. Model 6) is better than the asymmetric model (i.e. Model 2).

Combining the eight Taylor rule exchange rate models, the models with heterogeneous coefficients explain the exchange rate changes best. Due to the insignificant real exchange rate, symmetric models are better than asymmetric models. Moreover, the adjusted R-square statistic suggests models with house prices as a representation of the wealth effect are better than models with stock prices.

For the US-Australia exchange rate, although the *t*-statistics are insignificant for most of the variables in our models, the real exchange rate and house prices are significant. So, we can conclude that the house price is an important variable in explaining exchange rate movements in Australia. The adjusted R-square suggests the best model is the asymmetric model with heterogeneous coefficients (see model 10). In this model, exchange rate movements are mainly explained by the house price and real exchange rate.

Moreover, from the above Tables, It is noticeable that a common features shared by both wealth effect representations is that in all the models studied, the coefficients on the interest rate smoothing factor are low in absolute value. This means change in smoothing factor has only little effect on the exchange rate movement.

**Table 4-23 Estimation of Taylor rule exchange rate models for the UK - heterogeneous coefficients with house price**

| | *Model 2* | *Model 6* | *Model 10* | *Model 14* |
|---|---|---|---|---|
| $c$ | 0.171* | -0.088 | 0.047* | 0.024* |
| $\pi_t$ | -0.683 | -1.034 | -0.553 | -1.471* |
| $\tilde{\pi}_t$ | 1.009* | 1.244* | 1.213* | 1.196* |
| $y_t$ | -0.175 | 0.369 | -0.850* | -0.129 |
| $\tilde{y}_t$ | 1.955* | 1.517* | 1.776* | 0.783 |
| $\tilde{q}_t$ | -0.244* | - | -0.286* | - |
| $i_{t-1}$ | -0.01* | -0.00 | - | - |
| $\tilde{i}_{t-1}$ | -0.000 | -0.004 | - | - |
| $w_t$ | 0.501* | 0.199 | 0.370** | 0.187 |
| $\tilde{w}_t$ | 0.192** | 0.256** | -0.111 | -0.104 |
| ***Dummies*** | 11.399* | 1.826** | 21.760* | 4.136* |
| ***R-squared*** | 0.438 | 0.193 | 0.350 | 0.143 |
| ***Adj. R-squared*** | 0.354 | 0.081 | 0.294 | 0.078 |
| $\hat{\sigma}$ | 0.042 | 0.050 | 0.044 | 0.050 |
| ***Log likelihood*** | 209.501 | 188.648 | 201.063 | 185.168 |
| ***F-statistic*** | 5.072* | 0.595 | 4.827* | 3.197* |

*Note*: table show coefficient of the variable over the entire sample period. Models are estimated by OLS where standard errors have been Newey-West corrected. Dummies is the *F*-statistics for jointly significance of dummy variable. $\hat{\sigma}$ is the standard error of the regression. *F*-statistics is the Wald test for coefficient equality restriction discussed later in this section. *and **means significance at 5% and 1% significant level, respectively.

**Table 4-24 Estimation of Taylor rule exchange rate models for the UK - homogeneous coefficients with house price**

| | *Model 4* | *Model 8* | *Model 12* | *Model 16* |
|---|---|---|---|---|
| $c$ | 0.077* | -0.008 | 0.083* | -0.002 |
| $\tilde{\pi}_t - \pi_t$ | -0.135 | -0.064 | -0.010 | 0.055 |
| $\tilde{y}_t - y_t$ | 1.054 | 0.476 | 1.140 | 0.564 |
| $\tilde{q}_t$ | -0.157* | - | -0.155* | - |
| $\tilde{i}_{t-1} - i_{t-1}$ | 0.003 | 0.003 | - | - |
| $\tilde{w}_t - w_t$ | -0.136 | -0.166 | -0.113 | -0.145 |
| ***R-squared*** | 0.150 | 0.049 | 0.124 | 0.026 |
| ***Adj. R-squared*** | 0.111 | 0.015 | 0.093 | -0.001 |
| $\hat{\sigma}$ | 0.049 | 0.052 | 0.050 | 0.052 |
| ***Log likelihood*** | 185.654 | 179.223 | 183.931 | 177.785 |

*Note*: see notes on table 4-17.

**Table 4-25 Estimation of Taylor rule exchange rate models for the Sweden - heterogeneous coefficients with house price**

| | ***Model 2*** | ***Model 6*** | ***Model 10*** | ***Model 14*** |
|---|---|---|---|---|
| $\boldsymbol{c}$ | -0.072 | -0.072 | -0.020** | -0.021** |
| $\boldsymbol{\pi_t}$ | 1.249* | 1.250* | 1.063** | 1.054** |
| $\boldsymbol{\tilde{\pi}_t}$ | -1.077* | -1.078* | -0.373 | -0.336 |
| $\boldsymbol{y_t}$ | -0.096 | -0.095 | 0.276 | 0.293 |
| $\boldsymbol{\tilde{y}_t}$ | -0.860** | -0.851* | -0.911** | -1.005** |
| $\boldsymbol{\tilde{q}_t}$ | -0.007 | - | 0.067 | - |
| $\boldsymbol{i_{t-1}}$ | -0.001 | -0.001 | - | - |
| $\boldsymbol{\tilde{i}_{t-1}}$ | 0.005* | 0.005* | - | - |
| $\boldsymbol{w_t}$ | -0.821** | -0.819** | -0.822* | -0.831* |
| $\boldsymbol{\tilde{w}_t}$ | 0.332** | 0.329** | 0.132 | 0.152 |
| ***Dummies*** | 5.061* | 5.563* | 0.345 | 0.345 |
| ***R-squared*** | 0.237 | 0.237 | 0.144 | 0.141 |
| ***Adj. R-squared*** | 0.139 | 0.147 | 0.071 | 0.076 |
| $\boldsymbol{\hat{\sigma}}$ | 0.055 | 0.055 | 0.057 | 0.057 |
| ***Log likelihood*** | 177.938 | 177.936 | 171.355 | 171.121 |
| ***F-statistic*** | 1.355 | 1.400 | 2.056 | 2.171** |

*Note*: see notes on table 4-17.

**Table 4-26 Estimation of Taylor rule exchange rate models for the Sweden - homogeneous coefficients with house price**

| | ***Model 4*** | ***Model 8*** | ***Model 12*** | ***Model 16*** |
|---|---|---|---|---|
| $\boldsymbol{c}$ | 0.002 | 0.002 | 0.006 | 0.006 |
| $\boldsymbol{\tilde{\pi}_t - \pi_t}$ | -0.309 | -0.240 | -0.141 | -0.071 |
| $\boldsymbol{\tilde{y}_t - y_t}$ | -0.611** | -0.722* | -0.606** | -0.718** |
| $\boldsymbol{\tilde{q}_t}$ | 0.124 | - | 0.125 | - |
| $\boldsymbol{\tilde{i}_{t-1} - i_{t-1}}$ | 0.003 | 0.003 | - | - |
| $\boldsymbol{\tilde{w}_t - w_t}$ | 0.275** | 0.294* | 0.235** | 0.254** |
| ***R-squared*** | 0.080 | 0.067 | 0.048 | 0.035 |
| ***Adj. R-squared*** | 0.038 | 0.033 | 0.014 | 0.009 |
| $\boldsymbol{\hat{\sigma}}$ | 0.058 | 0.058 | 0.059 | 0.059 |
| ***Log likelihood*** | 167.184 | 166.379 | 165.234 | 164.443 |

*Note*: see notes on table 4-17.

**Table 4-27 Estimation of Taylor rule exchange rate models for the Australia - heterogeneous coefficients with house price**

| | ***Model 2*** | ***Model 6*** | ***Model 10*** | ***Model 14*** |
|---|---|---|---|---|
| $\boldsymbol{c}$ | -0.071* | 0.012 | -0.075* | -0.000 |
| $\boldsymbol{\pi_t}$ | 0.635 | -0.110 | 0.550* | -0.119 |
| $\boldsymbol{\tilde{\pi}_t}$ | -0.057 | 0.408 | -0.184 | -0.018 |
| $\boldsymbol{y_t}$ | -0.618 | -0.289 | -0.761 | -0.485 |
| $\boldsymbol{\tilde{y}_t}$ | -0.540 | -0.567 | -0.542 | -0.606 |
| $\boldsymbol{\tilde{q}_t}$ | -0.168* | - | -0.172* | - |
| $\boldsymbol{i_{t-1}}$ | -0.001 | -0.001 | - | - |
| $\boldsymbol{\tilde{i}_{t-1}}$ | -0.000 | -0.002 | - | - |
| $\boldsymbol{w_t}$ | 0.391** | 1.102** | 1.408* | 1.143* |
| $\boldsymbol{\tilde{w}_t}$ | 1.375* | 0.238 | 0.396* | 0.228 |
| ***Dummies*** | 14.509* | 12.587* | 12.655* | 12.796* |
| ***R-squared*** | 0.230 | 0.146 | 0.227 | 0.130 |
| ***Adj. R-squared*** | 0.164 | 0.082 | 0.176 | 0.082 |
| $\boldsymbol{\hat{\sigma}}$ | 0.058 | 0.061 | 0.057 | 0.061 |
| ***Log likelihood*** | 169.545 | 163.634 | 169.324 | 162.569 |
| ***F-statistic*** | 5.423* | 3.254* | 4.906* | 2.240** |

*Note*: see notes on table 4-17.

**Table 4-28 Estimation of Taylor rule exchange rate models for the Australia - homogeneous coefficients with house price**

| | ***Model 4*** | ***Model 8*** | ***Model 12*** | ***Model 16*** |
|---|---|---|---|---|
| $\boldsymbol{c}$ | -0.033* | -0.005 | -0.032* | -0.005 |
| $\boldsymbol{\tilde{\pi}_t - \pi_t}$ | -0.058 | 0.103 | -0.025 | 0.107 |
| $\boldsymbol{\tilde{y}_t - y_t}$ | 0.000 | -0.132 | 0.032 | -0.131 |
| $\boldsymbol{\tilde{q}_t}$ | -0.08** | - | -0.084* | - |
| $\boldsymbol{\tilde{i}_{t-1} - i_{t-1}}$ | 0.000 | 0.000 | - | - |
| $\boldsymbol{\tilde{w}_t - w_t}$ | -0.018 | -0.043 | 0.016 | -0.042 |
| ***R-squared*** | 0.039 | 0.004 | 0.038 | 0.004 |
| ***Adj. R-squared*** | -0.005 | -0.032 | 0.004 | -0.022 |
| $\boldsymbol{\hat{\sigma}}$ | 0.064 | 0.064 | 0.063 | 0.064 |
| ***Log likelihood*** | 156.833 | 154.782 | 156.816 | 154.781 |

*Note*: see notes on table 4-17.

*Test of the coefficient equality restrictions*

Furthermore, the Wald-test is employed to test whether heterogeneous models can be equally represented by corresponding homogenous models. In theory the null hypothesis assumes the coefficients should be equal and oppositely signed for most of the explanatory variables. Recall the general Taylor rule exchange rate:

$$\Delta s_{t+1} = \alpha - \alpha_{u\pi}\pi_t + \alpha_{f\pi}\tilde{\pi}_t - \alpha_{uy}y_t + \alpha_{fy}\tilde{y}_t - \alpha_{uw}w_t + \alpha_{fw}\widetilde{w}_t + \alpha_q\tilde{q}_t - \alpha_{ui}i_{t-1} + \alpha_{fi}\tilde{\imath}_{t-1} + \eta_t \quad (4\text{-}18)$$

Then the following Wald test is:

$$H_0\colon\ \alpha_{fi} - \alpha_{ui} = 0 \ \ for\ all\ i$$
$$H_1\colon\ \alpha_{fi} - \alpha_{ui} \neq 0 \quad (4\text{-}19)$$

The results are shown in the last row of each table.

For the US-UK models with stock prices, apart from the specification of the asymmetric model with no smoothing, the null hypothesis of equal parameter coefficients cannot be rejected. Therefore, the estimated weights for the UK are not very different from the US and the unrestricted model can be replaced by the corresponding restricted model. In addition, in the two models where dummy variables are jointly insignificant (see Table 4-19 and Table 4-23), we can use the corresponding restricted models. For the US-UK model with house prices, the restriction holds only for the symmetric model with smoothing.

For the US and Swedish data, at the 5% significance level, the restricted model can be replaced by the unrestricted model in all cases. However, for the Australian exchange rate series, most of the models with house prices do not support the equal parameter null when measured at the 10% significance level.

A summary of the results are shown in Table 4-29. In general, when stock prices are used to represent the wealth effect, most of the unrestricted models are identical to the restricted models, while in most of the models with house prices, the unrestricted models cannot be replaced by restricted models. Although restrictions hold for about half of the cases we studied, the results are still reported here as both restricted and unrestricted cases are to be used for forecasting in next chapter.

**Table 4-29 Test of Equal coefficients**

| | ***asymmetric with smoothing*** | | | ***symmetric with smoothing*** | | |
|---|---|---|---|---|---|---|
| | *US-UK* | *US-SD* | *US-AUS* | *US-UK* | *US-SD* | *US-AUS* |
| ***stock*** | equal | equal | equal | equal | equal | Not (at 10%) |
| ***house*** | Not | equal | Not | equal | equal | Not |
| | ***asymmetric with no smoothing*** | | | ***symmetric with no smoothing*** | | |
| | *US-UK* | *US-SD* | *US-AUS* | *US-UK* | *US-SD* | *US-AUS* |
| ***stock*** | not | equal | equal | equal | equal | equal |
| ***house*** | Not | equal | Not | Not | Not (at 10%) | Not (at 10%) |

*Note*: this is summarised results of coefficient equality restriction. The corresponding *F*-statistics can be found in last row of Table 4-17 to Table 4-28.

## 4.7 Summary of results

The conclusions drawn from the empirical analysis in Section 4.6.3 can be summarised as follows:

Firstly, we have noted that most of the results show that, contrary to the popular view, macroeconomic fundamentals do offer explanatory power for exchange rate modelling. However, despite the finding that various macroeconomics variables are able to explain exchange rate movements, there is no single set of variables consistently emerging across models and countries as the most relevant ones.

Secondly, including the wealth effect improved the overall performance of the Taylor rule exchange rate forecasting equation derived by Molodtsova and Papell

(2009). However, the role and importance of the wealth effect differ across countries. For the US and UK, stock prices are a more significant wealth factor when modelling the exchange rate, while for the US-Sweden model, the house price plays the most important role in explaining exchange rate changes. In the US-Australian case, the stock price is an important factor in determining exchange rate movements, whilst the house price only becomes significant when the models are asymmetric and with heterogeneous coefficients. The Taylor rule exchange rate models incorporating wealth effects are the most relevant for studying the US-UK exchange rate. In this case, most of the variables are significantly different from zero. The R-square statistic in one specification is as high as 43.8%.

A reason for the different wealth effects predominating in some countries but not others is due to the structural differences across these countries. Classified by financial structure, empirical research has identified that the UK, US, Australia as well as Sweden are all market based economies (Ludwig and Sløk, 2004; Levine, 2002), Levine (2002, p.2) defines the market-based financial systems: 'securities markets share centre stage with banks, in terms of getting society's savings to firms, exerting corporate control, and easing risk management'. So, it is not surprising stock prices have an important effect on the UK and Australia exchange rate, as capital flows between their equity markets. However, our results for the Swedish exchange rate give different conclusions with exchange rates more influenced by house prices. After careful study of the wealth structure of Sweden, we found that there are several reasons why house price are more significant than stock prices in explaining the US-Swedish exchange rate movements. Firstly, Swedish stock market wealth counts only as a small proportion of the total household financial wealth, as estimated by Chen (2006), 0.08-0.2% of total financial wealth is from the stock market. In contrast, housing wealth takes a larger proportion of Swedish non-stock wealth. According to Chen (2006), about 50-70% of non-stock wealth is coming from housing for the period of 1980 to 2004. As housing wealth takes up a large proportion of household asset wealth, changes in house prices will have a more significant impact on consumption. Secondly, house prices often indirectly influence consumption through credit loans, as it is often used as collateral. Sweden has a large and liquid housing finance market, its mortgage bond market ranks as the third in Europe.[43] The nature of that mortgage bond price is highly influenced by changes in house price making house prices an important determining factor. This is further explained by Maclennan et al. (1998), who have shown that Sweden is operating under a mortgage bank system.[44] Therefore, changes in house prices will have large debt effects. Moreover, there is a weak correlation between the Swedish stock market index and financial wealth. Barot and Yang (2002) found that house prices Granger causes financial wealth for Sweden and it is the house prices that cause household debt for Sweden.

Last but not least, the coefficient signs and magnitudes vary across different models. This confirms the model assumption on the sign of coefficients made by Molodtsova *et al.* (2008).

[43] This is taken from Housing statistics in European Union;

[44] Mortgage bank systems raise funds by selling bonds to institutional investors, with fixed rate mortgages.

# Chapter 5 Forecasting of the Exchange Rate Model

## 5.1 Introduction

Statistical inference conducted in Chapter 4 offers information about the empirical performance of the Taylor rule with a wealth effect when modelling the exchange rate. In general, we have found some support for the Taylor rule based exchange rate and especially the wealth effect in our data analysis. Such macroeconomic fundamentals do play a role in explaining changes in exchange rates. However, the evidence is not very strong. Although wealth effects are significant, they do not play a consistent role across the countries studied, as stock prices predominate in some countries and house prices in others. Overall, a superior model does not emerge across the countries and time periods studied. The next step is to assess its usefulness in forecasting three exchange rate out-of-sample, as in Molodtsova and Papell (2009). It is well known in the forecasting literature, a model may offer stable coefficients and fulfil all the assumptions underlying the estimation but have poor out-of-sample performance for an extended period of time, as discussed by Stock and Watson (2003) and Timmermann (2006). In order to see whether our Taylor rule model has some properties that makes it a good forecasting model, we will be investigating its out-of-sample forecasting ability in this chapter.

The aim of this chapter is to examine two issues. The first being whether including a wealth effect in the regression (i.e. stock prices or house prices) improves the forecasting performance of the econometric model proposed by Molodtsova and Papell (2009). The second is to investigate how the use of different forecasting window sizes affects the out-of-sample exchange rate predictability. Results show that our out-of-sample results are significant for all studied countries at short-term horizons. We find that our Taylor rule models significantly outperform the random walk over different forecast windows for one-quarter-ahead forecasts when the U.S is the base currency.

The remainder of this chapter is organized as follows. Section 2 presents the theoretical models based on Molodtsova and Papell (2009). Section 3 discusses the various test statistics used in this study and section 4 describes the methodology used in examining the forecasting performance. Section 5 presents the data and main empirical analysis. The last section concludes and suggests further areas of study.

## 5.2 The Models

Recall from the previous empirical chapter, our Taylor rule forecasting model has taken the form of:

$$\Delta s_{t+1} = \alpha_m + \beta_m X_{m,t} + \eta_{m,t+1} \tag{5-1}$$

where $\Delta s_{t+1}$ is the change in the log of the nominal exchange rate determined as the domestic price of foreign currency. $X_{m,t}$ is a vector contains different economic variables. A general form of our forecasting model is given by the following equation:

$$\begin{aligned}\Delta s_{t+1} = \alpha - \alpha_{u\pi}\pi_t + \alpha_{f\pi}\tilde{\pi}_t - \alpha_{uy}y_t + \alpha_{fy}\tilde{y}_t - \alpha_{uw}w_t \\ + \alpha_{fw}\widetilde{w}_t + \alpha_q\tilde{q}_t - \alpha_{ui}i_{t-1} + \alpha_{fi}\tilde{\imath}_{t-1} + \eta_t\end{aligned} \tag{5-2}$$

Depending on different assumptions about the coefficients, there are sixteen models embedded in the above equation.

Model 1: asymmetric, with smoothing, heterogeneous coefficients with stock prices
$X_{1,t} \equiv [c \quad \pi_t \quad \tilde{\pi}_t \quad y_t \quad \tilde{y}_t \quad \tilde{q}_t \quad i_{t-1} \quad \tilde{\imath}_{t-1} \quad w_t(stock) \quad \widetilde{w}_t(stock)]$
Model 2: asymmetric, with smoothing, heterogeneous coefficient with house prices
$X_{2,t} \equiv [c \quad \pi_t \quad \tilde{\pi}_t \quad y_t \quad \tilde{y}_t \quad \tilde{q}_t \quad i_{t-1} \quad \tilde{\imath}_{t-1} \quad w_t(house) \quad \widetilde{w}_t(house)]$

Model 3: asymmetric, with smoothing, homogeneous coefficient with stock prices

$X_{3,t} \equiv [c \quad \pi_t - \tilde{\pi}_t \quad y_t - \tilde{y}_t \quad \tilde{q}_t \quad i_{t-1} - \tilde{\imath}_{t-1} \quad w_t(s) - \widetilde{w}_t(s)\,]$

Model 4: asymmetric, with smoothing, homogeneous coefficient with house prices

$X_{4,t} \equiv [\,c \quad \pi_t - \tilde{\pi}_t \quad y_t - \tilde{y}_t \quad \tilde{q}_t \quad i_{t-1} - \tilde{\imath}_{t-1} \quad w_t(h) - \widetilde{w}_t(h)\,]$

Model 5: Symmetric with smoothing, heterogeneous coefficient with stock prices

$X_{5,t} \equiv [c \quad \pi_t \quad \tilde{\pi}_t \quad y_t \quad \tilde{y}_t \quad i_{t-1} \quad \tilde{\imath}_{t-1} \quad w_t(stock) \quad \widetilde{w}_t(stock)]$

Model 6: Symmetric with smoothing, heterogeneous coefficient with house prices

$X_{6,t} \equiv [c \quad \pi_t \quad \tilde{\pi}_t \quad y_t \quad \tilde{y}_t \quad i_{t-1} \quad \tilde{\imath}_{t-1} \quad w_t(house) \quad \widetilde{w}_t(house)]$

Model 7: Symmetric with smoothing, homogeneous coefficient with stock prices

$X_{7,t} \equiv [\,c \quad \pi_t - \tilde{\pi}_t \quad y_t - \tilde{y}_t \quad i_{t-1} - \tilde{\imath}_{t-1} \quad w_t(s) - \widetilde{w}_t(s)\,]$

Model 8: Symmetric with smoothing, homogeneous coefficient with house prices

$X_{8,t} \equiv [\,c \quad \pi_t - \tilde{\pi}_t \quad y_t - \tilde{y}_t \quad i_{t-1} - \tilde{\imath}_{t-1} \quad w_t(h) - \widetilde{w}_t(h)\,]$

Model 9: Asymmetric, no smoothing, heterogeneous coefficient with stock prices

$X_{9,t} \equiv [c \quad \pi_t \quad \tilde{\pi}_t \quad y_t \quad \tilde{y}_t \quad \tilde{q}_t \quad w_t(stock) \quad \widetilde{w}_t(stock)]$

Model 10: Asymmetric, no smoothing, heterogeneous coefficient with house prices

$X_{10,t} \equiv [c \quad \pi_t \quad \tilde{\pi}_t \quad y_t \quad \tilde{y}_t \quad \tilde{q}_t \quad w_t(house) \quad \widetilde{w}_t(house)]$

Model 11: Asymmetric, no smoothing, homogeneous coefficient with stock prices

$X_{11,t} \equiv [\,c \quad \pi_t - \tilde{\pi}_t \quad y_t - \tilde{y}_t \quad \tilde{q}_t \quad w_t(s) - \widetilde{w}_t(s)\,]$

Model 12: Asymmetric, no smoothing, homogeneous coefficient with house prices

$X_{12,t} \equiv [\,c \quad \pi_t - \tilde{\pi}_t \quad y_t - \tilde{y}_t \quad \tilde{q}_t \quad w_t(h) - \widetilde{w}_t(h)\,]$

Model 13: Symmetric, no smoothing, heterogeneous coefficient with stock prices

$X_{13,t} \equiv [c \quad \pi_t \quad \tilde{\pi}_t \quad y_t \quad \tilde{y}_t \quad w_t(stock) \quad \widetilde{w}_t(stock)]$

Model 14: Symmetric, no smoothing, heterogeneous coefficient with house prices

$X_{14,t} \equiv [c \quad \pi_t \quad \tilde{\pi}_t \quad y_t \quad \tilde{y}_t \quad w_t(house) \quad \widetilde{w}_t(house)]$

Model 15: Symmetric, no smoothing, homogeneous coefficient with stock prices

$X_{15,t} \equiv [\,c \quad \pi_t - \tilde{\pi}_t \quad y_t - \tilde{y}_t \quad w_t(s) - \widetilde{w}_t(s)\,]$

Model 16: Symmetric, no smoothing, homogeneous coefficient with house prices

$X_{16,t} \equiv [\,c \quad \pi_t - \tilde{\pi}_t \quad y_t - \tilde{y}_t \quad w_t(h) - \widetilde{w}_t(h)\,]$

From the previous chapter, we found the dummy variables account for the corresponding structural breaks are jointly insignificant in some models. For example, Model 5 and Model 13 in the case of the US/UK exchange rate, Model 9, Model 10, Model 13 and Model 14 in the case of US/Sweden exchange rate. However, the Wald-test from the previous chapter gives us some information about the equality of the coefficients in the models. At the five percentage significance level, results from the Wald-test show that these unrestricted models have coefficients equal to their corresponding restricted model.

Therefore, for those of the unrestricted models containing jointly insignificant dummy variables and which can be replaced by a restricted model, we will generate forecasts based on the restricted models only in order to save space. For example, for the US-UK model with stock prices, forecasting is based on six models. The other countries will be done in a similar manner.

Based on this principle, 42 forecasts will be generated in this study. These are 14 forecasts for the US/UK exchange rate; 12 forecasts for the US/Sweden exchange rate and 16 forecasts for the US/Australia exchange rate.

## 5.3 Discussion of the test statistics used in exchange rate forecasting

Before describing the methods used in this study, I will discuss the most widely used test statistics in the literature. In general, there is no ideal test for evaluating exchange rate models out-of-sample.

### 5.3.1 MSPE approach

Traditionally, the procedure introduced by Diebold and Mariano (1995) and West (1996) (DMW) along with the Theil's U test statistic are the preferred minimum MSPE out-of-sample test statistics used in the exchange rate forecasting literature.

The DMW use sample MSPEs to construct *t*-type statistics which are assumed to be asymptotically normal. The Theil's U gives a ratio of the forecasting model's statistics against that of the random walk model. As noted by Ince (2014) and Rogoff and Stavrakeva (2008), both these tests can be interpreted as minimum MSPE tests, as they test whether the random walk model and the structural model have equal MSPE.

However, since the seminal paper of Clark and McCracken (2001), Clark and McCracken (2005) and Clark and West (2007), there has been some criticism of the DMW method as to its providing a biased MSPE in comparison to methods for nested models. Analytically, the asymptotic distributions of sample and population difference between the two MSPEs are not identical, namely the sample difference between the two MSPEs is biased downward from zero. They show that the sample difference between the two MSPEs is uncentered under the null and, therefore, the MSPE of the random walk model would be smaller than that of a linear model. The intuition behind this result is as follows. If the null is true, estimating the alternative model introduces noise into the forecasting process because it is trying to estimate parameters which are zero in population. Use of the noisy estimate will lead to a higher estimated MSPE and, as a result, the sample MSPE of the alternative model will be higher by the amount of estimation noise. This is relevant to this research, since when the null hypothesis is a random walk and the alternative hypothesis is a linear model, the two models are always nested.

In order to solve this problem, Clark and West (2007) propose a procedure called the CW procedure. It adjusts the DMW statistic for testing the null of the equal predictive ability of a linear model and random walk. This is a preferable methodology when two models are nested.[45] It corrects the size distortion of the DMW statistics by

[45] One alternative approach is to compute bootstrap distributions for the DMW statistics. This strategy has been used by Mark (1995), Kilian (1999), Ince (2014) among others. However, the CW procedure is more popular and powerful than the bootstrapping technique. The bootstrap technique is considered to be more difficult to implement (Rogoff and Stravrakeva, 2008).

taking into account the upward shift in the sample MSPE of the alternative models. Results from simulations by Clark and West (2007) show that: when the parsimonious model is a random walk, the adjusted CW test statistic is asymptotically standard normal. The asymptotically normal test statistic results in a properly-sized test.

The CW procedures have two limitations. One is the CW procedure is only well defined in a rolling framework where the size of the in-sample portion of the series is kept fixed (Rogoff and Stavrakeva, 2008). Since rolling regressions with fixed portions are used in this study, it is not a concern here.

Another shortcoming of the CW test is that it cannot always be interpreted as the minimum MSPE test as with the DMW test. As proved by Rogoff and Stavrakeva (2008), testing whether the exchange rate is a random walk is the same as testing whether the mean square error of the random walk is equal to the mean square error of the structural model when we perform in-sample testing using OLS, because OLS minimizes the mean square error. However, this is different in out-of-sample cases. When testing predictability out-of-sample, testing whether the nature of exchange rate is a random walk is not the same as testing whether the MSPE of a random walk is smaller than the MSPE of a structural model due to potential forecast bias. Therefore, in the presence of forecast bias, the DMW test and the CW test have a different null. As shown by Rogoff and Stavrakeva (2008) and Ince (2014), the DMW statistics are used to test whether the MSPE from the model based forecast have equal MSPEs to a random walk, while the CW null hypothesis tests whether the true nature of the exchange rate follows a random walk.

Molodtsova and Papell (2012) further classified the two test statistics: the CW method is used for judging predictability whilst the DMW test statistic gives evidence of forecasting ability. The term “predictability” as a shorthand for “out-of-sample predictability” in the sense used by Clark and West (2006). It tests whether the regression coefficient $\beta$ is zero rather than whether the sample MSPE from the model-based forecast is smaller than the sample MSPE from the random walk forecast. Therefore, it is possible to have a situation where we reject the random walk null in favour of the structural model alternative in the case where the MSPE of the random walk forecast is smaller than MSPE of the structural model. In the above situation, we have no problem in an econometric context of testing for predictability, but it becomes problematic if one is interpreting the results as evidence of forecasting ability.

In order to solve the problem of testing for forecasting ability in nested models, we will use the ratio of the MSPE of the structural model to the MSPE of the random walk model (i.e. Theil's U) in addition to the CW statistic. The CW statistic provides evidence of predictability for the model and the Theil's U ratio gives evidence of whether our forecast model is better than the random walk.

### 5.3.2 Direction of Change Criterion

The above tests evaluate the acceptability of a set of forecasts by computing a global distance between actual data and the associated forecasts through a smooth continuous function of forecast errors, i.e. mean square error. While these tests may be convenient to establish some comparison between alternative models, it is not so useful for judging the quality of a single set of forecasts.

In order to evaluate whether a set of forecasts is acceptable, an althernative approach is also used to testing the quality of the forecasts. These tests consider the null hypothesis of " the set of forecasts is not useful" and can be implemented by the porpular Pesaran and Timmermann (1992) test.

The shortcoming of this appraoch is it may be selecting a model which performs well only in predicting small changes, however, this selected model may perform poorly in predicting large changes (Rogoff and Stavrakeva, 2008).

## 5.4 Methodology

In order to test the out-of-sample predictability, we use similar techniques as Molodtsova and Papell (2009). The statistics are constructed within the context of a rolling regression. For each of the four countries we analyse, using data over the period 1975Q1 to 1999Q4 for estimation in the case of the stock price models and data over the period 1980Q1 to 1999Q4 for estimation when house prices have been used. The rest of the data will be retained so we can compare our forecasting result with it. For rolling regressions, a moving window of 100 observations (model with stock prices) and 80 observations (model with house prices) is used first to estimate the models and then to generate the one quarter ahead out-of-sample forecast. Then, the in-sample part of the sample is updated with the first data point dropped, one additional data point at the end of our sample is then added, and models re-estimated again. So the size of our in-sample portion of the series is kept fixed. At each step, a one-step-ahead prediction for the exchange rates will be generated. The loop continues until 2008Q3. The last 100 or 80 observations will be used to generate forecasts for the last date 2008Q4. In total, 36 one-quarter-ahead forecasts will be derived with this model.

In line with previous work, we will use the random walk model as one of our benchmark naïve models.[46] In addition, we will also use the same sixteen models without the wealth factors as another comparator. The latter provide useful information on whether the wealth effect improves our forecasting performance.

### 5.4.1 Forecast Comparison based on the MSPE

To compare the out-of-sample forecasting ability of the models, we will focuses on the comparison of the Mean Squared Prediction Errors (MSPE) of the models. This

[46] We choose the random walk with no drift to be one of the benchmark models because according to Meese and Rogoff (1983a, b) it is the toughest benchmark to beat.

method takes the difference between the actual and predicted values of exchange rates as a forecasting error and has been popular for comparing out-of-sample exchange rate forecasting since Meese and Rogoff (1983a) and Meese and Rogoff (1983b).

$$MSPE = \frac{1}{n}\sum_{t=1}^{n}(y_t - \hat{y}_t)^2 \qquad (5\text{-}3)$$

Where $y_t$ is the actual value at time $t$ ; $\hat{y}_t$ is the forecast value at time $t$. The MSPE of each forecasting model is compared with a random walk model and models without a wealth effect:

Model 17: Random walk without drift: $\Delta s_{t+1} = 0$ (5-4)

We are testing the null hypothesis that the sample estimates of MSPEs are equal against the alternative that the MSPE of our linear model is smaller than the MSPE of the random walk model. If the MSPE of our forecasting model is smaller than the MSPE of the random walk or models without the wealth effect, then we say our forecasting model outperforms the random walk or models without a wealth effect.

### ***Theil's U (TU)***

Theil's U-statistic was developed by Theil et al. (1966). It is a relatively simple and accurate MSPE test used to compare forecasted result with the results from a random walk forecasting methods. It gives more weight to large errors by squaring the deviation. The formula for calculating Theil's U statistic is:

$$U = \sqrt{\frac{\sum_{t=1}^{n-1}\left(\frac{\hat{y}_{t+1} - y_{t+1}}{y_t}\right)^2}{\sum_{t=1}^{n-1}\left(\frac{y_{t+1} - y_t}{y_t}\right)^2}} \qquad (5\text{-}5)$$

where $y_t$ is the actual value at time $t$, $\hat{y}_t$ is the forecasted value at time $t$, $n$ is the number of the observations (Wheelwright et al., 1998).

The TU test statistics can be interpreted as dividing the square root of the MSPE of the structural model by the square root of the MSPE of the random walk model (i.e. U=1 model). If U is equal to one, it means the forecasting from the structural model is as good as the random walk model. If U greater than one, the forecasting results from the structural model are worse than the random walk model, so there is no point using the proposed forecast model. If U is smaller than one, we conclude the structural model provides more accurate forecasts than the random walk model.

### *Clark and West (CW) Test*

The CW statistic is a modified DMW test and is one of the most popular out-of-sample test statistics for nested models.[47]

Assuming that we have a sample size of $T + 1$ observations, the first $R$ observations are used for estimation; the last $P$ observations are used for forecasting. If we fix our moving window at the beginning of the sample to size $R$, then the first forecast is made for observation $R + 1$, the next is for $R + 2$, and so on; the final one is for $T + 1$. So we have: $T + 1 = R + P$ where in our case, $T + 1 = 136\ or\ 116$, $R = 100\ or\ 80$ and $P = 36$.

The specification of the CW test is to test whether the exchange rate is a random walk. As presented in Clark and West (2007), Let:

- Model 1: the parsimonious model

[47] Two models are nested if both contain the same terms and one has at least one additional term.

- Model 2: the larger, nested model[48]
- $\hat{y}_{1t,t+1}$ : The one-period-ahead forecast in period $t$ from Model 1
- $\hat{y}_{2t,t+1}$ : The one-period-ahead forecast in period $t$ from Model 2
- $y_{t+1}$ : The actual value at $t+1$ (i.e. in this paper, $y_{t+1} = \Delta s_{t+1}$)

So, the corresponding one-period-ahead forecast errors from the two models are:

$$\hat{e}_{1t,t+1} = y_{t+1} - \hat{y}_{1t,t+1}; \qquad \hat{e}_{2t,t+1} = y_{t+1} - \hat{y}_{2t,t+1}; \tag{5-6}$$

Then, we can define the sample MSPEs as the sample average of $\left(y_{t+1} - \hat{y}_{1t,t+1}\right)^2$ and $\left(y_{t+1} - \hat{y}_{2t,t+1}\right)^2$. i.e.

$$MSPE_1 = \hat{\sigma}_1^2 = P^{-1} \sum_{t=T-p+1}^{T} \left(y_{t+1} - \hat{y}_{1t,t+1}\right)^2 \tag{5-7}$$

$$MSPE_2 = \hat{\sigma}_2^2 = P^{-1} \sum_{t=T-p+1}^{T} \left(y_{t+1} - \hat{y}_{2t,t+1}\right)^2 \tag{5-8}$$

Clark and West (2007) build on the DMW statistics by including an adjustment term in order to overcome the fact that the DMW test statistic is undersized under the null hypothesis. Since Model 1 is a parsimonious model, the $MSPE_1$ expected to be smaller than $MSPE_2$ under the null. Clark and West (2007) adjust for this upward shift in $MSPE_2$ by deducting an adjustment term:

$$Adj = P^{-1} \sum_{t=T-p+1}^{T} \left(\hat{y}_{1t,t+1} - \hat{y}_{2t,t+1}\right)^2 \tag{5-9}$$

So we have:

[48] Model 2 reduces to model 1 if some parameters in model 2 are set to zero.

$$\hat{\sigma}_2^2 - Adj = P^{-1}\sum_{t=T-p+1}^{T}\left(y_{t+1} - \hat{y}_{2t,t+1}\right)^2 - P^{-1}\sum_{t=T-p+1}^{T}\left(\hat{y}_{1t,t+1} - \hat{y}_{2t,t+1}\right)^2 \tag{5-10}$$

We are proposing to test the null hypothesis of equal MSPE and the alternative that model 2 has a smaller MSPE than model 1:

$$\begin{aligned} &\mathrm{H}_0\text{: } MSPE_1 = (MSPE_2 - Adj) \qquad (i.e. \hat{\sigma}_1^2 - (\hat{\sigma}_2^2 - Adj) = 0) \\ &\mathrm{H}_1\text{: } MSPE_1 > (MSPE_2 - Adj) \qquad (i.e.\ \hat{\sigma}_1^2 - (\hat{\sigma}_2^2 - Adj) > 0) \end{aligned} \tag{5-11}$$

For computational convenience, Clark and West (2007) define:

$$\begin{aligned} \hat{f}_{t+1} = \hat{\sigma}_1^2 - (\hat{\sigma}_2^2 - Adj) \\ = \left(y_{t+1} - \hat{y}_{1t,t+1}\right)^2 \\ - \left[\left(y_{t+1} - \hat{y}_{2t,t+1}\right)^2 - \left(\hat{y}_{1t,t+1} - \hat{y}_{2t,t+1}\right)^2\right] \end{aligned} \tag{5-12}$$

After some simplification:

$$\hat{f}_{t+1} = 2\left(\hat{y}_{1t,t+1} - y_{t+1}\right)\left(\hat{y}_{1t,t+1} - \hat{y}_{2t,t+1}\right) \tag{5-13}$$

Let:

$$\bar{f} = MSPE_1 - (MSPE_2 - Adj) = P^{-1}\sum_{t=T-p+1}^{T}\hat{f}_{t+1} \tag{5-14}$$

Therefore, the null hypothesis we are testing becomes $H_0\text{: } \bar{f} = 0$ vs $H_1\text{: } \bar{f} > 0$

So, testing for equal MSPE can be simplified by regressing $\hat{f}_{t+1}$ on a constant and testing the resulting *t*-statistics for a zero coefficient. It is rejected if the statistic is greater than $+1.282$ (for a one side 0.10 test) or $+1.645$ (for a one side 0.05 tests).

For one-step-ahead forecast errors, the usual least squares standard error can be used (Clark and West, 2007).

### 5.4.2 Pesaran-Timmermann (PT) Test

The Pesaran-Timmermann test is a directional prediction test which focuses on correctly forecasting the direction of change in the varaibles under consideration. The null hypothesis is that there is no relationship between the actual and predicted directional changes.

It is a distribution free procedure based on the proportion of times that the direction of change in $y_t$ is correctly predicted in the sample. As speicified in (Pesaran and Timmermann, 1992), let:

- $\mathrm{y_t}$ : Actual value at time t
- $\hat{y}_t$ : The predictor value of $y_t$ based on information available at time $t-1$
- $n$ : Total number of observations in the forecast series

Set:

$$Y_t = \begin{cases} 1 & y_t > 0 \\ 0 & elasewise \end{cases} \qquad \hat{Y}_t = \begin{cases} 1 & \hat{y}_t > 0 \\ 0 & elasewise \end{cases}$$
$$Z_t = \begin{cases} 1 & y_t\hat{y}_t > 0 \\ 0 & elasewise \end{cases} \tag{5-15}$$

Let $P_y = Pr(y_t > 0)$, $P_{\hat{y}} = Pr(\hat{y}_t > 0)$ and $\hat{P}$ be the proportion of time that the sign of $y_t$ is correctly predicted. On the assumption that $y_t$ and $\hat{y}_t$ are independently distributed of each other, the number of correct sign prediction has a binominal distribution with $n$ trials and success probability equal to:

$$P_* = \Pr(Z_t = 1) = Pr(y_t \hat{y}_t > 0)$$
$$= Pr(y_t > 0,\ \hat{y}_t > 0) + Pr(y_t < 0,\ \hat{y}_t < 0) \qquad (5\text{-}16)$$
$$= P_y P_{\hat{y}} + (1 - P_y)(1 - P_{\hat{y}})$$

Estimating these probabilities with their samples, we have:

$$\hat{P}_y = \frac{\sum_{t=1}^{n} y_t}{n}\ ,\ \hat{P}_{\hat{y}} = \frac{\sum_{t=1}^{n} \hat{y}_t}{n}\ ,\ \ \hat{P}_* = \hat{P}_y \hat{P}_{\hat{y}} + (1 - \hat{P}_y)(1 - \hat{P}_{\hat{y}}) \qquad (5\text{-}17)$$

Under the null hypothesis that $y_t$ and $\hat{y}_t$ are independently distributed, i.e. $\hat{y}_t$ has no power in forecasting $y_t$, the test statistic is:

$$PT = \frac{\hat{P} - \hat{P}_*}{\left(v\hat{a}r(\hat{P}) - v\hat{a}r(\hat{P}_*)\right)^{1/2}} \qquad (5\text{-}18)$$

where

$$v\hat{a}r(\hat{P}) = n^{-1}\hat{P}_*(1 - \hat{P}_*), \qquad (5\text{-}19)$$

$$v\hat{a}r(\hat{P}_*) = n^{-1}(2\hat{P}_y - 1)^2 \hat{P}_{\hat{y}}(1 - \hat{P}_{\hat{y}}) + n^{-1}(2\hat{P}_{\hat{y}} - 1)^2 \hat{P}_y(1 - \hat{P}_y) + 4n^{-2}\hat{P}_y \hat{P}_{\hat{y}}(1 - \hat{P}_y)(1 - \hat{P}_{\hat{y}}) \qquad (5\text{-}20)$$

In the case when $P_y$ and $P_{\hat{y}}$ are known, the predictive failure test can be formed by:

$$PT = \left\{\frac{P_*(1 - P_*)}{n}\right\}^{-1/2} (\hat{P} - P_*) \qquad (5\text{-}21)$$

Pesaran-Timmermann show that PT statistics converge to a standard normal distribution. The critical values at 95% and 99% are 1.64 and 2.33 respectively.

### 5.4.3 Tests Specification in This Study

In this study, the MSPE, Theil's U and CW statistics are used for two types of models:

*Case One*: testing the predictive ability of our Taylor rule model against a random walk without drift;

- Model 1: random walk model (i.e. parsimonious model)
- Model 2: Taylor rule model with wealth effect

*Case Two*: test whether forecast performance of the model is improved by including a wealth effect:

- Model 1: Taylor rule model without wealth effect (parsimonious model)
- Model 2: Taylor rule model with wealth effect

In the case of a random walk without drift, the one period ahead forecast value equals zero (i.e. $\hat{y}_{1t,t+1} = 0$). Therefore, the MSPE is the sample average of the actual change in the exchange rate value:

$$MSPE_1 = \hat{\sigma}_1^2 = P^{-1} \sum_{t=T-p+1}^{T} (y_{t+1})^2 \tag{5-22}$$

In CW statistic $$\hat{f}_{t+1} = 2(y_{t+1})(\hat{y}_{2t,t+1}) \tag{5-23}$$

## 5.5 Forecasting Results

### 5.5.1 The Taylor Rule Model with Wealth Effects Tested against a Random Walk without Drift

Table 5-1 to Table 5-3 present one-quarter-ahead out-of-sample forecasts of the exchange rate. The first column of each table reports the MSPEs of the linear models.

The second column reports the ratio of the out-of-sample MSPEs of the linear model to that of the random walk model and the third column reports test statistics using the CW test with asymptotic critical values when the model under the null is the random walk without drift.

Combining all the specifications of the Taylor-rule fundamentals and the two types of wealth effect, the overall results across countries suggest evidence of short-term predictability in the Taylor rule model. However, strong evidence of predictability is found in less than 50% of the models when measured using either Theil's U ratio or the CW statistics. We find that the MSPE ratios are below one for 18 models. So, these models present evidence of better forecasting than the random walk for 18 out of the 42 specifications. The CW statistics give lower rates of predictability than the results from Theil's U ratio, with 13 specifications outperforming the random walk models. This difference in results is not surprising because these statistics test slightly different null hypothesis (i.e. equal MSPEs vs. the exchange rate is a random walk).

Focusing on the CW statistics, we find that the Taylor rule with a smoothing factor performs relatively better out-of-sample than models with no smoothing specification. This is because models with smoothing factors are taking into account the smooth change in interest rates and are better at reflecting how monetary policy is conducted. Of the 13 models which present evidence of better forecasting than the random walk, 12 of them contain a lagged interest rate. This result is again not surprising and is consistent with the previous literature. For example, Molodtsova and Papell (2009) have found models with smoothing are better than models with no smoothing in predicting the exchange rate. Results from Theil's U statistics further confirm the impression that models with smoothing have better predictability. Furthermore, it shows models with heterogeneous coefficients perform slightly better out-of-sample than the Taylor rule that restricts the coefficients. This result is also consistent with Molodtsova (2008), Molodtsova and Papell (2009) and Moura (2010).

In general, it is difficult to find a model which consistently outperforms a random walk across all countries for those models. We have observed that results from forecasting are similar with in-sample estimation, however, results regarding the best performing model are different across countries. These results follow the direction of many others in the literature where Taylor rule models have some predictability, but there are differences in performance according to the model specification and there is no specification consistently winning across countries and over time (e.g. Gloria, 2010; Yu-Chin and Kenneth, 2012).

Focusing first on the case of the pound/dollar exchange rate shown in Table 5-1, results from the TU ratio agree with the CW test statistics. The most successful model is the asymmetric model with smoothing and heterogeneous coefficients (see Model 2). In this model, house prices are used to represent the wealth effect. The next most successful model is the same model but with the wealth effect represented by stock prices (see Model 1). This agrees with our result from in-sample estimation, with the best model being the asymmetric model with smoothing and heterogeneous coefficients.

For the UK's and Sweden's exchange rates, several of the models consistently provide evidence of predictability. For example, models with the asymmetric specification that includes the real exchange rate in the forecasting regression and interest rate smoothing factors. In these models, the Theil's U ratio is less than unity and CW statistic is significant at the 10% significance level for all cases with heterogeneous coefficients (see Model 1 and Model 2) and one case with homogenous coefficients when house prices represent the wealth effect (see Model 4). The possible reasons may be that the two countries, UK and Sweden, have similar monetary policies and exchange rate frameworks during the period studied.

**Table 5-1 Forecasts of UK/US exchange rate: Random walk**

| | *MSPE* | *Theil's U* | *CW* |
|---|---|---|---|
| *Model 1* | **0.001166** | **0.857187** | **1.67641*** |
| *Model 2* | **0.001140** | **0.838073** | **1.94050*** |
| *Model 3* | 0.001489 | 1.094641 | 1.10773 |
| *Model 4* | 0.001323 | 0.972606 | 1.96271* |
| *Model 6* | 0.001619 | 1.190211 | 0.98984 |
| *Model 7* | 0.001382 | 1.015980 | 1.38696** |
| *Model 8* | 0.001365 | 1.003482 | 1.63543** |
| *Model 9* | 0.001300 | 0.955698 | 1.13156 |
| *Model 10* | 0.001423 | 1.046121 | 1.20158 |
| *Model 11* | 0.001348 | 0.990985 | 1.21887 |
| *Model 12* | 0.001372 | 1.008628 | 1.68863* |
| *Model 14* | 0.001536 | 1.129193 | 0.97060 |
| *Model 15* | 0.001390 | 1.021861 | 1.20715 |
| *Model 16* | 0.001416 | 1.040975 | 1.22065 |

*Note:* Theil's U and CW are test values relative to the benchmark of the random walk model. Significance levels at 90% and 95%, are denoted by one and two stars, respectively. For CW statistics, the null hypothesis is rejected if the statistic is greater than $+1.282$ (for a one side 0.10 test) or $+1.645$ (for a one side 0.05 tests). The random walk MSPE: 0.001360.

Table 5-2 shows the relative performance of the models for the Swedish/US exchange rate. Firstly, as with the results from the estimation that found support for house prices in representing the wealth effect in the Taylor rule specifications, models with house prices also perform better than models with stock prices in predicting the exchange rate over the sample period. The TU ratio and CW statistic both show the best performing model is the symmetric model with smoothing and heterogeneous coefficients. However, the two test methods give different conclusions regarding the second most successful models. The TU ratio shows the next most successful model is the asymmetric model with heterogeneous coefficients, while the CW statistic shows it is the symmetric model with no real exchange rate and with restricted coefficients. Although results regarding the best performing model are slightly different between the two methods, all these models show evidence of strong out-of-sample predictability for when the null is a random walk.

**Table 5-2 Forecasts of UK/US exchange rate: Random walk**

| | *MSPE* | *Theil's U* | *CW* |
|---|---|---|---|
| *Model 1* | 0.003823 | 0.994278 | 1.48817** |
| *Model 2* | 0.003491 | 0.907932 | 1.86850* |
| *Model 3* | 0.004073 | 1.059298 | -1.00164 |
| *Model 4* | 0.003627 | 0.943303 | 1.77308* |
| *Model 5* | 0.003816 | 0.992458 | 1.52400** |
| *Model 6* | **0.003438** | **0.894148** | **1.88862*** |
| *Model 7* | 0.004155 | 1.080624 | -1.56422 |
| *Model 8* | 0.003582 | 0.931599 | 1.87713* |
| *Model 11* | 0.004142 | 1.077243 | -1.55889 |
| *Model 12* | 0.003891 | 1.011964 | 0.80149 |
| *Model 15* | 0.004245 | 1.104031 | -2.19379 |
| *Model 16* | 0.003854 | 1.002341 | 0.84685 |

*Note:* Theil's U and CW are test values relative to the benchmark of the random walk model. Significance levels at 90% and 95%, are denoted by one and two stars, respectively. For CW statistics, the null hypothesis is rejected if the statistic is greater than $+1.282$ (for a one side 0.10 test) or $+1.645$ (for a one side 0.05 tests). The random walk MSPE: 0.003845.

However, Australia represents a different picture. Table 5-3 presents results for the Australia/ US data. We find from the CW statistics, forecasts based on fundamentals offer little improvement over the random walk at the one-quarter-horizon. This result is consistent with the Meese-Rogoff (1983) findings from over three decades ago. A number of papers have shown that fundamental variables are of little help in explaining short-term fluctuations in the Australian dollar, for example, Molodtsova and Papell (2009), Engel et al. (2007) and Ince (2014) have used various techniques in making exchange rate forecasts and found the models cannot beat a random walk.

While we do not have a definitive answer, we can think of three possible reasons for this exception. Firstly, this may come from differences in market structure, the types of products the country specializes in or the central bank's reserve management policy response. Secondly, there may be a key short-run explanatory variable omitted from our Taylor rule model. As Shown by Chen (2002) and Gloria (2010), commodity prices reflect the nature of the Australian exchange rate and it is important in helping to explain exchange rate movements for this country. Finally, forecasting performance from exchange rate models may depend on the choice of how the sample is split into the in-sample and out-of-sample portions (Rossi and Inoue, 2012).[49] The estimation window contains a period of time where the country is not operating under a free-floating exchange rate system. Australia only abandoned its management of the exchange rate after the end of 1983. So using data cover multiple exchange rate regimes may be another possible reason for the poor predictability.

**Table 5-3 Forecasts of Australia/US exchange rate: Random walk**

| | ***MSPE*** | ***Theil's U*** | ***CW*** |
|---|---|---|---|
| *Model 1* | 0.007225 | 1.240219 | -0.41961 |
| *Model 2* | 0.006503 | 1.116283 | 0.68795 |
| *Model 3* | 0.005896 | 1.012087 | 0.71188 |
| *Model 4* | 0.006248 | 1.072510 | -0.33956 |
| *Model 5* | 0.006325 | 1.085728 | 0.10021 |
| *Model 6* | 0.005726 | 0.982906 | 1.19977 |
| *Model 7* | 0.005666 | 0.972606 | **1.37201**** |
| *Model 8* | 0.006170 | 1.059121 | -2.21093 |
| *Model 9* | 0.006221 | 1.067876 | 0.66462 |
| *Model 10* | 0.005168 | 0.887121 | 1.12626 |
| *Model 11* | 0.005819 | 0.998870 | 0.94648 |
| *Model 12* | 0.006279 | 1.077832 | -0.72976 |
| *Model 13* | 0.005690 | 0.976726 | 1.22755 |
| *Model 14* | 0.004875 | **0.836826** | 1.07925 |
| *Model 15* | 0.005730 | 0.983592 | 1.06044 |
| *Model 16* | 0.006162 | 1.057748 | -2.51471 |

*Note:* Theil's U and CW are test values relative to the benchmark of the random walk model. Significance levels at 90% and 95%, are denoted by one and two stars, respectively. For CW statistics, the null hypothesis is rejected if the statistic is greater than +1.282 (for a one side 0.10 test) or +1.645 (for a one side 0.05 tests). The random walk MSPE: 0.005826.

[49] This will be discussed further in detail in section 5.5.3.

Regarding the best performing model, the TU ratio and CW statistics give very different conclusion. 7 out of 16 models have a TU ratio less than one, indicate that the MSPE of these structural models are less than the MSPE of the random walk. The lowest TU ratio is given by the symmetric model with no smoothing and heterogeneous coefficients, and with house prices representing the wealth effect (see Model 14). However, when measured by the CW statistic, only one Taylor rule model shows evidence of predictability. This is the symmetric one with smoothing and homogeneous coefficients, along with stock prices (see Model 7).[50]

The accuracy of the forecasts achieved from the structural models for the dollar against the UK pound sterling, Swedish krona and Australian dollar is shown in Figure 5-1 to Figure 5-3. These figures make apparent how the exchange rate forecasts from the best model track the actual exchange rate. Since results based on different models are similar, to conserve space, only results for the most successful specifications are reported here.

Since all exchange rates are expressed as dollar price per foreign currency, a positive value will represent dollar depreciation and a negative value will represent a dollar appreciation. Since exchange rate changes are forecast to be zero in the random walk model, the zero line represents the forecasted exchange rate from the random walk model.

Several results can be draw from the figures. Firstly, it can be seen clearly from these figures, our Taylor rule models track the actual changes better than the random walk in general. The figure based on the structural model represents considerable variability relative to the random walk. Therefore, for the three dollar exchange rates, the figures suggest contradicting viewpoints, as with Meese and Rogoff (1983a, b) that economic fundamentals have little predictive power for exchange rate.

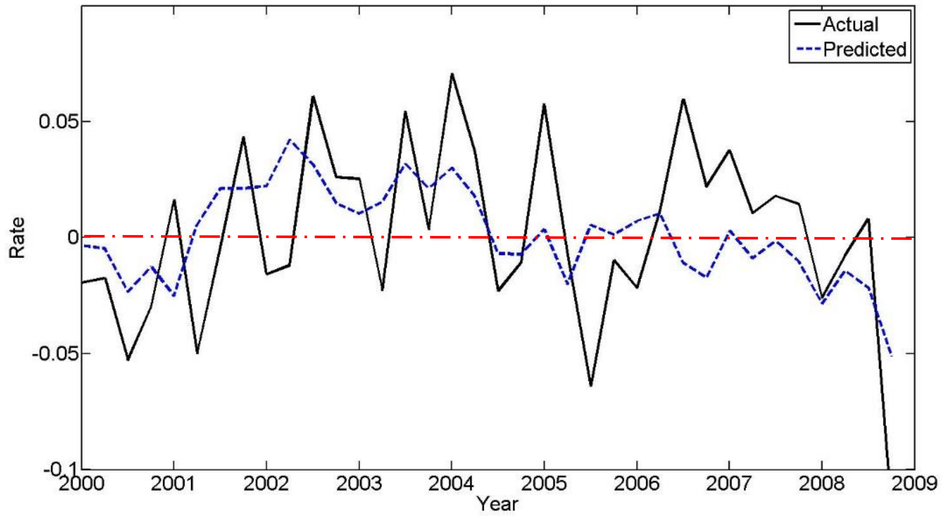
[50] The reason for this difference in results is explained in section 5.3.1.

Secondly, we observe that the actual exchange rate movement shows much more variability than the predicted movement from the Taylor rule fundamentals, especially in the case of Australia. For the US-UK exchange rate, the predicted changes from the Taylor rule fundamentals model are similar to those actual changes, although they are less variable. The model incorrectly predicts changes from 2000:Q4 to 2001:Q2, then starts to track the pattern of the actual exchange rate changes. The figures for the US/Australia exchange rate confirms our results from the TU ratio and CW test by showing the forecasts from the Taylor rule fundamentals have low predictability over actual exchange rate changes. The possible reason for the low predictability is as explained above. Moreover, the lower variability may be contributed to from noise that is unrelated to our fundamentals or missing fundamentals (Sarno and Valente, 2009).

There is also a large difference between the predicted and actual exchange rate changes for all countries we analyse by the end of 2008. This result is, however, not surprising as it coincides with the most volatile period of the recent financial crisis. During that period of worldwide economic instability, it would be naïve to expect exchange rates to follow traditional economic fundamentals.[51]

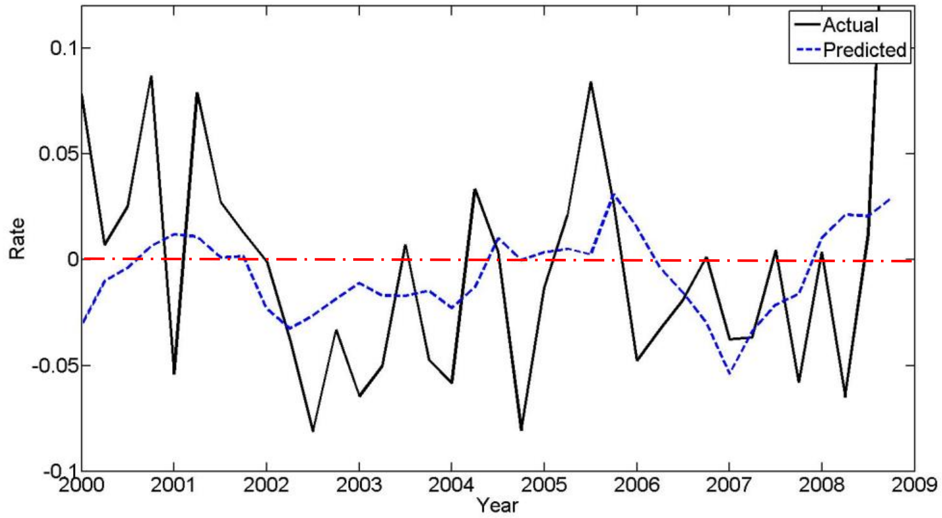
[51] Molodtsova and Papell (2012) have given a detailed study of exchange rate forecasting during this period of the financial crisis.

**Figure 5-1 Actual and Predicted Changes in US/UK Exchange Rate**



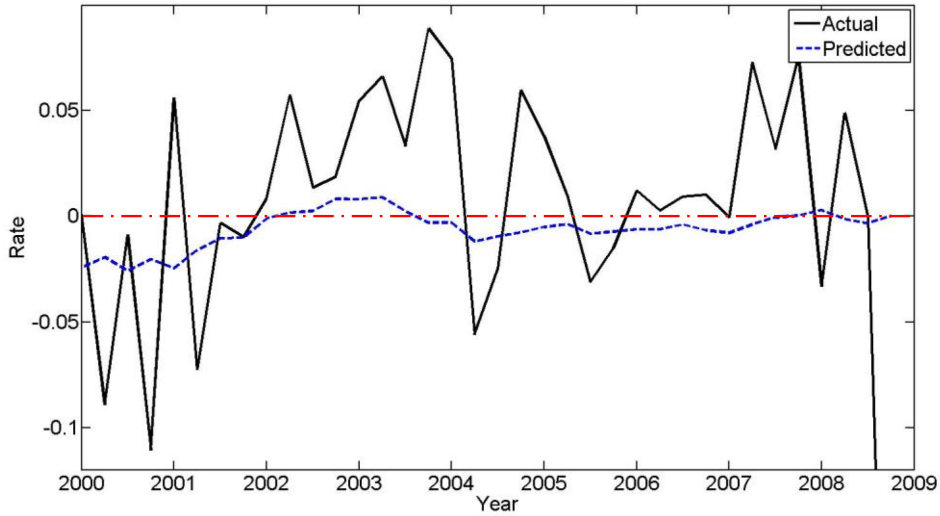

*Note*: these graphs show accuracy of the forecasts achieved from the structural models for the dollar against the UK pound sterling. Exchange rate are defined as the U.S. price per unit of foreign currency. Since results based on different models are similar, to conserve space, only results for the most successful specification are reported here. A higher number thus represent a depreciation of the U.S. dollar. The line at zero represent forecast of a random walk.

**Figure 5-2 Actual and Predicted Changes in US/Sweden Exchange Rate**




*Note*: see notes on Figure 5-1.

**Figure 5-3 Actual and Predicted Changes in US/Australia Exchange Rate**




*Note*: these graphs show accuracy of the forecasts achieved from the structural models for the dollar against the Australia dollar. Exchange rate are defined as the U.S. price per unit of foreign currency. Since results based on different models are similar, to conserve space, only results for the most successful specification are reported here. A higher number thus represent a depreciation of the U.S. dollar. The line at zero represent forecast of a random walk.

### 5.5.2 Forecast Performance against Models without Wealth

So far I have provided evidence that the null hypothesis of no out-of-sample predictability for exchange rate can be rejected, although not consistently, using Taylor rule models incorporating two different wealth effects. In this section, we are going to investigate whether the Taylor rule without a wealth effect models can be improved by the models with a wealth effect on the basis of their out-of-sample exchange rate forecasts.[52]

Table 5-4 to Table 5-6 reports the results where the evaluation of the performance is based on the one-quarter-ahead forecast of the Molodtsova and Papell (2009) model

[52] Out-of-sample performance may vary depending on the different comparison benchmark (Inoue and Killian, 2005 and Engel et al.,2007).

(i.e. Taylor rule exchange rate model without a wealth effect). The first and second column reports the MSPE of the linear models without and with the wealth effect respectively. The ratios of out-of-sample MSPEs of the two linear models are reported in the third column. A value below one indicates that models with wealth effects forecast exchange rates better than the ones without. The last column reports the CW statistics. Large CW statistics mean that null of equal predictability is rejected in favour of the alternative, that models with wealth effects forecast better than models without. For this section, we focus on the proportion of models with Theil's U ratio below 1 and CW statistics above 1.282.

As expected, models presented better out-of-sample predictability when wealth effects have been included. Combining all Taylor rule specifications, the models with wealth effects significantly outperform models without them for all the countries studied and in 22 out of 42 cases when measured by the CW statistics. MSPE ratios also present evidence of lower forecast error when the wealth effect is being included in 30 out of 42 specifications.

The evidence is particularly strong for the Australian exchange rate. The MSPE ratio is below one for 12 out of the 16 specifications and CW statistics show that in 10 out of 16 specifications, models with wealth effects outperform models without. Combined with the result where the benchmark model is a random walk, although the CW statistic indicates only one model outperforms the random walk in predicting the exchange rate, predictability is clearly improved when wealth effects are taken into account.

**Table 5-4 Forecasts of UK/US exchange rate: without wealth effect**

| | *MSPE (without wealth)* | *MSPE (with wealth)* | *Theil's U* | *CW* |
|---|---|---|---|---|
| *Model 1* | 0.001407 | 0.001166 | 0.828714 | 2.97040* |
| *Model 2* | 0.001200 | 0.001140 | 0.950000 | 1.66541* |
| *Model 3* | 0.001622 | 0.001489 | 0.918002 | 1.95877* |
| *Model 4* | 0.001345 | 0.001323 | 0.983643 | 0.94715 |
| *Model 6* | 0.001264 | 0.001619 | 1.280854 | -2.08770 |
| *Model 7* | 0.001586 | 0.001382 | 0.871375 | 2.02995* |
| *Model 8* | 0.001358 | 0.001365 | 1.005155 | 0.05303 |
| *Model 9* | 0.001315 | 0.001300 | 0.988593 | 0.81376 |
| *Model 10* | 0.001203 | 0.001423 | 1.182876 | 0.10999 |
| *Model 11* | 0.001448 | 0.001348 | 0.930939 | 1.67889* |
| *Model 12* | 0.001414 | 0.001372 | 0.970297 | 1.26197 |
| *Model 14* | 0.001224 | 0.001536 | 1.254902 | -1.18648 |
| *Model 15* | 0.001579 | 0.001390 | 0.880304 | 1.85138* |
| *Model 16* | 0.001445 | 0.001416 | 0.979931 | 0.85138 |

*Note:* Theil's U and CW are test values relative to the benchmark. The benchmark model is the corresponding Taylor rule models without wealth effect. Significance levels at 90% and 95%, are denoted by one and two stars, respectively. For CW statistics, the null hypothesis is rejected if the statistic is greater than +1.282 (for a one side 0.10 test) or +1.645 (for a one side 0.05 tests).

**Table 5-5 Forecasts of Sweden/US exchange rate: without wealth effect**

| | *MSPE (without wealth)* | *MSPE (with wealth)* | *Theil's U* | *CW* |
|---|---|---|---|---|
| *Model 1* | 0.003850 | 0.003823 | 0.992987 | 0.87556 |
| *Model 2* | 0.003895 | 0.003491 | 0.896277 | 1.33453** |
| *Model 3* | 0.003848 | 0.004073 | 1.058472 | -1.72654 |
| *Model 4* | 0.003826 | 0.003627 | 0.947987 | 1.55901** |
| *Model 5* | 0.003867 | 0.003816 | 0.986811 | 1.20165 |
| *Model 6* | 0.003850 | 0.003438 | 0.892987 | 1.34457** |
| *Model 7* | 0.003898 | 0.004155 | 1.065931 | -2.00486 |
| *Model 8* | 0.003799 | 0.003582 | 0.942880 | 1.70415* |
| *Model 11* | 0.003934 | 0.004142 | 1.052872 | -0.95984 |
| *Model 12* | 0.003996 | 0.003891 | 0.973724 | 1.62781** |
| *Model 15* | 0.00398 | 0.004245 | 1.066583 | -1.37467 |
| *Model 16* | 0.003974 | 0.003854 | 0.969804 | 1.81828* |

*Note:* see notes on Table 5-4.

**Table 5-6 Forecasts of Australia/US exchange rate: without wealth effect**

| | *MSPE (without wealth)* | *MSPE (with wealth)* | *Theil's U* | *CW* |
|---|---|---|---|---|
| *Model 1* | 0.007589 | 0.007225 | 0.952036 | 1.5347** |
| *Model 2* | 0.007039 | 0.006503 | 0.923853 | 1.43305** |
| *Model 3* | 0.006517 | 0.005896 | 0.904711 | 2.40982* |
| *Model 4* | 0.006137 | 0.006248 | 1.018087 | -1.47474 |
| *Model 5* | 0.006717 | 0.006325 | 0.941641 | 1.64009** |
| *Model 6* | 0.006132 | 0.005726 | 0.933790 | 0.95835 |
| *Model 7* | 0.006204 | 0.005666 | 0.913282 | 2.11926* |
| *Model 8* | 0.005890 | 0.006170 | 1.047538 | -2.22200 |
| *Model 9* | 0.006805 | 0.006221 | 0.914181 | 2.22047* |
| *Model 10* | 0.006314 | 0.005168 | 0.818499 | 1.61034** |
| *Model 11* | 0.006401 | 0.005819 | 0.909077 | 2.27631* |
| *Model 12* | 0.006175 | 0.006279 | 1.016842 | -1.15389 |
| *Model 13* | 0.00626 | 0.005690 | 0.908946 | 2.18539* |
| *Model 14* | 0.005683 | 0.004875 | 0.857822 | 1.05557 |
| *Model 15* | 0.006256 | 0.005730 | 0.915921 | 2.10900* |
| *Model 16* | 0.005880 | 0.006162 | 1.047959 | -2.11222 |

*Note:* see notes on Table 5-4.

Combining the results from Table 5-4 to Table 5-6 where the null is the Taylor rule models without wealth effects, with results from Table 5-1 to Table 5-3 where the null hypothesis is a random walk, it is evident that some models outperform both the random walk and models without a wealth effect. For the UK, three models pass the double tests (see Model 1, 2 and 7). Results are generally mixed with regard to which wealth effects are better. For Sweden, four models pass the double tests. These are Model 2, 4, 6 and 8, all these models use house price to represent wealth effects. This is consistent with our result from in-sample estimation. For Australia, the only model which outperforms the random walk (see Model 7) also has predictability improved when stock prices are added to the forecast equation.

### 5.5.3 Tests over Different Forecast Windows

In section 5.5.1, I discussed the possible reasons for the poor performance of our Taylor rule forecasting equation in the case of Australia. One of the possible contributions to this is the choice of our forecasting window. Previously, we have used a window size of 100 and 80 observations in our quarterly data due to data availability. The start of the data for the estimation are 1975:Q1 and 1980Q1. This estimation window contains a period of time where the Australian exchange rate was fixed. In fact, it was from December 1983 onwards that Australia's exchange rate entered a period of free-floating and this has continued until the present. Use of different window sizes may lead to different empirical results. As shown by Rossi and Inoue (2012), Using different estimation window sizes, data will produce very large difference in out-of-sample forecasting performance.

In this section, a reduced moving window of 64 is going to be used to estimate models and produce one-quarter-ahead out-of-sample forecasts. The in-sample estimation will use data over the period 1983Q4 to 1999Q4 and the rest are saved for comparing out-of-sample forecasting. Same as before, 36 forecasts will be generated based on a rolling regression.

The forecasting results of our linear models based on this new rolling window size against the random walk null are shown in Table 5-7 for Australia. The results show using data from 1983Q4 has clearly improved exchange rate predictability. The MSPE ratios decreased in most of the specifications and the number of models with significant CW statistics increases to five.

The results for the models with coefficient restrictions in home and foreign parameters are not as strong as those without coefficient restrictions. In only one homogenous specification, do the CW statistics show evidence of exchange rate predictability.

The evidence of predictability is stronger with the stock prices than with the house prices as the wealth effect. This is the same result as we found for the OLS estimation. With the stock price, the no predictability null can be rejected at the 5 percent level for all specifications with heterogeneous coefficients and one specification with homogenous coefficients. None of the models with house prices have shown evidence of predictability. The strongest evidence of predictability comes from the simplest specifications where the exchange rate only responds to inflation, output gap and stock prices (see Model 13 and 15).

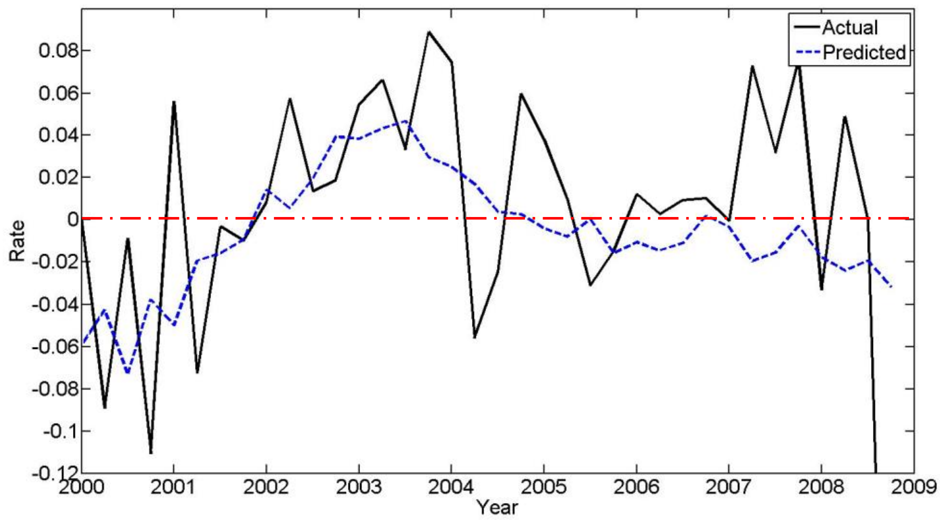
**Table 5-7 Forecasts of Australia/US exchange rate: Random walk (From 1983Q4)**

| | ***MSPE*** | ***Theil's U*** | ***CW*** |
|---|---|---|---|
| *Model 1* | 0.006375 | 1.094311 | 1.50462* |
| *Model 2* | 0.005775 | 0.991317 | 0.90355 |
| *Model 3* | 0.006233 | 1.069935 | -0.30963 |
| *Model 4* | 0.007420 | 1.273692 | -1.65244 |
| *Model 5* | 0.005554 | 0.953381 | 1.83561* |
| *Model 6* | 0.005351 | 0.918534 | 1.05650 |
| *Model 7* | 0.006078 | 1.043329 | -0.63376 |
| *Model 8* | 0.007205 | 1.236786 | -1.54363 |
| *Model 9* | 0.005916 | 0.892957 | 1.52690* |
| *Model 10* | 0.005202 | 1.015520 | 0.91753 |
| *Model 11* | 0.006041 | 1.036977 | 0.09733 |
| *Model 12* | 0.007262 | 1.246570 | -1.85988 |
| *Model 13* | 0.005102 | 0.875792 | **1.99363*** |
| *Model 14* | 0.004776 | **0.819832** | 1.18171 |
| *Model 15* | 0.005543 | 0.951492 | 1.96617* |
| *Model 16* | 0.006664 | 1.143919 | -1.72073 |

*Note:* Theil's U and CW are test values relative to the benchmark of the random walk model. Significance levels at 90% and 95%, are denoted by one and two stars, respectively. For CW statistics, the null hypothesis is rejected if the statistic is greater than +1.282 (for a one side 0.10 test) or +1.645 (for a one side 0.05 tests). The random walk MSPE: 0.005825.

The figure of actual and predicted exchange rate changes further confirms our results of an improved forecasting performance. As illustrated in Figure 5-4, the model estimated using data after 1983 track the actual changes better than the random walk and better than the model estimated using mixed exchange rate regime data.

**Figure 5-4 Actual and Predicted Changes in US/Australia Exchange Rate**




*Note*: these graphs show accuracy of the forecasts achieved from the structural models for the dollar against the Australia dollar. Exchange rate are defined as the U.S. price per unit of foreign currency. Since results based on different models are similar, to conserve space, only results for the most successful specification are reported here. A higher number thus represent a depreciation of the U.S. dollar. The line at zero represent forecast of a random walk.

### 5.5.4 Result from PT tests

Table 5-8 reports the results from our analysis of the predictive power of our exchange rate models for different countries. The column labelled "directional accuracy" shows the percentage of exchange rate changes that were accurately forecast by different models over the one quarter interval. The PT statistics provide information in accessing predictability in the direction of exchange rate changes. Results in general vary with different countries.

For the UK and US exchange rates, the rolling predictions get the sign of the exchange rate changes right in at least 50% of all quarters over the period 2000 to 2008. Model 15 (symmetric, no smoothing, heterogeneous coefficient with stock prices) gives the highest directional prediction accuracy, with 72.2 percent of actual exchange rate changes correctly predicted. The PT test statistics show that only for 4 out 14 models, are the predicted changes significantly associated with the actual changes. A common feature shared by these is they are all symmetric models (i.e. with no real exchange rate). For the PT results confirmed by directional accuracy, models with significant PT statistics have higher fractions of successful directional prediction than others.

**Table 5-8 Non-parametric Statistics for the Pesaran-Timmermann (PT) test**

| | ***UK*** | | ***Sweden*** | | ***Australia*** | |
|---|---|---|---|---|---|---|
| | *Directional Accuracy* | *PT statistic* | *Directional Accuracy* | *PT statistic* | *Directional Accuracy* | *PT statistic* |
| *Model 1* | 58.3% | 1.1198 | 44.4% | -1.0934 | 47.2% | -1.1931 |
| *Model 2* | 58.3% | 1.0306 | 63.9% | 1.7889* | 55.6% | -0.0926 |
| *Model 3* | 52.8% | 0.3912 | 33.3% | -2.1552 | 47.2% | 0.0401 |
| *Model 4* | 58.3% | 1.0725 | 58.3% | 1.1198 | 47.2% | -0.1173 |
| *Model 5* | - | - | 44.4% | -1.0934 | 69.4% | 2.3371** |
| *Model 6* | 61.1% | 1.4255 | 69.4% | 2.6186** | 55.6% | 0.0862 |
| *Model 7* | 61.1% | 1.5597 | 36.1% | -1.7889 | 52.8% | 1.1932 |
| *Model 8* | 66.7% | 2.3047* | 63.9% | 1.9270* | 33.3% | -1.8073 |
| *Model 9* | 55.6% | 0.6981 | - | - | 47.2% | -0.1173 |
| *Model 10* | 58.3% | 1.1198 | - | - | 63.9% | 1.1809 |
| *Model 11* | 50.0% | 0 | 33.3% | -2.2180 | 50.0% | 0.4887 |
| *Model 12* | 58.3% | 1.0725 | 52.8% | 0.3912 | 44.4% | -0.5462 |
| *Model 13* | - | - | - | - | 61.1% | 2.2986* |
| *Model 14* | 63.9% | 2.0641* | - | - | 58.3% | 1.3088 |
| *Model 15* | 72.2% | 3.2660** | 33.3% | -2.6701 | 58.3% | 1.7371* |
| *Model 16* | 58.3% | 1.8405* | 52.8% | 0.4282 | 30.6% | -2.2731 |

*Note:* Directional accuracy is the percentage of exchange rate changes that were accurately forecast. * and ** indicates model can correctly forecast the direction of change at 5% and 1% significant level. The critical values of PT-test at 95% and 99% are 1.64 and 2.33 respectively.

As can be seen from second panel of Table 5-8, the model which gives the best forecast of direction change for the Sweden/US exchange rate is the symmetric, no smoothing and homogeneous coefficient model with house prices to represent the wealth effect (see Model 6). It gives the highest fraction of successful directional prediction at 66.7%. The PT statistic is well above the 95% critical value for a one sided standard normal test and led to a strong rejection of the hypothesis that actual and predicted exchange rates are independently distributed.

The PT statistics show 5 models provide evidence of predictive power in exchange rate movements. We notice all these models have house prices representing the wealth effect. Therefore, exchange rate forecasting models incorporating house prices are more accurate in forecasting actual exchange rate changes. This agrees with our OLS estimation result: house prices are more relevant than stock prices in explaining changes in the exchange rate.

I have found in section 5.5.3 that forecasting based on data after 1983:Q4 are better in predicting the exchange rate for Australia, therefore, the PT test for Australia will use predicted exchange rate changes based on this reduced moving window.

For the Australian data, the Pesaran-Timmermann test statistics show that only Model 5, 13 and 15 have the PT statistics bigger than 1.65, and so we reject the null hypothesis of independence of real and predicted exchange rate movements for only these three models. Since Model 13 is an unrestricted version of Model 15, and Model 13 has a higher directional accuracy and PT statistic than Model 15, we conclude that symmetric models with homogenous coefficients and stock prices are better in predicting directional changes of the exchange rate for Australia.

From the above PT test results, we conclude that not all Taylor rule models are effective in predicting the direction of the exchange rate changes. For almost two thirds of the models studied, the direction of exchange rate change predicted from the Taylor rule models is uncorrelated with the actual directional changes. Among the three countries that have been studied, the PT statistics show that Taylor rule models give the highest predictive power for the UK/ US data. Model 15 in general works well for both the UK/US and Australia/US exchange rate predictions. However, neither of these models have significant PT statistics for the Sweden/US exchange rate.

Combining the results from the PT test with the results based on MSPE criterion, the results are most consistent when analysing Sweden's out-of-sample performance. Both criterions show that Taylor rule fundamentals models with house prices outperform the fundamental models with stock prices, and the best performing specification is the symmetric model with smoothing, heterogeneous coefficients and house prices (see Model 6). Results are less consistent when measuring forecasting performance for UK and Australia's exchange rate. For example, some of the models give evidence of predictability in the CW statistics are insignificant when measured by PT statistics.

### 5.5.5 Summary of the Results

Overall, taking together the results from section 5.5.1 to 5.5.4, it is clear that Taylor rule specifications with wealth effect can forecast some exchange rate with a reasonable degree of accuracy and offer significant outperformance over both a random walk and Taylor rule models without wealth effects. However, we note that such superior out-of-sample predictability of particular specifications are inconsistent and depend on the country being studied, sample periods and the choice between in-sample and out-of-sample periods and also the size of the rolling window used for estimation. This is not a surprising result and is in accordance with many studies in the literature (e.g. Molodtsova and Papell, 2009; Rogoff and Stavrakeva, 2008; Gloria, 2010; Galimberti and Moura, 2013 among others). As summarized by Stock and Watson (2003) and Rossi (2013):"which series predicts what, when, and where is itself difficult to predict: good forecasting performance by an indicator in one period seems to be unrelated to whether it is a useful predictor in a later period."

## 5.6 Conclusion

This study has contributed to the literature by extending the study of the out-of-sample exchange rate forecasting and Taylor rule models with wealth effects. Using a comprehensive dataset from 1975Q1 to 2008Q4, we examine the out-of-sample performance of the models with the Taylor rule fundamentals for the UK, Sweden and Australian exchange rates at one-quarter horizons.

The first purpose of this chapter is to investigate whether including wealth effects (i.e. stock prices or house prices) improves the forecasting performance of the econometric model proposed by Molodtsova and Papell (2009). The major result is that the inclusion of wealth effects as an additional variable can improve the predictive accuracy of some specifications. As with the result from the estimation of the model, models which incorporate stock prices outperform models with house prices in forecasting exchange rates for the UK and Australia, while in the case of Sweden's exchange rate, specifications with house prices have better predictability.

The second purpose of the study is to investigate how the use of different forecasting window sizes affects out-of-sample exchange rate predictability by looking at models for the USD/Australia exchange rate with Taylor rule fundamentals. There is stronger evidence of predictability at the one-quarter-ahead horizon when estimating the model using data after Australia moved to a free-floating exchange rate. This results confirms the criticism reported by Rogoff and Stavrakeva (2008) and Rossi and Inoue (2012): the robustness of out-of-sample predictability depends on the choice of window size, especially in the presence of structural breaks.

In line with previous results in the literature, short-term exchange rate predictability is found in some specifications. Furthermore, we find that several specifications not only provided strong evidence of exchange rate predictability over that found by the Molodtsova and Papell (2009) specifications, they also outperform a random walk by a significant amount. However, there is no single model consistently providing superior predictability across all countries and in all forecast horizons.

This study has many limitations that may lead to future studies. One important limitation is that we are using a linear single equation Taylor rule model. Recent studies on monetary policy have found that the non-linear Taylor rules are better in explaining monetary policy reaction functions of the central banks (e.g. Qin and Enders, 2008; Cukierman and Muscatelli, 2008). Therefore, it will be interesting to see whether a non-linear Taylor rule exchange rate model provides more support for exchange rate predictability. This will be studied in the next chapter.

# Chapter 6 A STR model of the Taylor rule Exchange rate Approach

## 6.1 Introduction

In recent years, nonlinear models have become more common in empirical economics. This trend has brought with it a growing number of studies aimed at estimating and forecasting economic variables with nonlinear models. Studies focusing on the nonlinear Taylor rule have been undertaken by Qin and Enders (2008), Martin and Milas (2004), Schaling (2004) among others. Within these studies, different approaches have been investigated and results in general suggested that the non-linear Taylor rules are better in explaining the monetary policy reaction functions of the central banks than the linear versions. Nevertheless, the unsolved exchange rate puzzle which mainly relies on the linearity assumption has been studied again in nonlinear models based on various theoretical and empirical motivations (e.g. McCallum, 1994; Baldwin, 1990; Lyons, 2001; Sarantis, 1999).[53] However, to our knowledge, there has been no attempt to connect both strands of the literature into one and exploit the possibility of nonlinearity in Taylor rule type exchange rate models. Therefore, it is of interest to summarize the two avenues of literatures and conduct a study to see whether a non-linear Taylor rule exchange rate model provides more support for exchange rate predictability.

The aim of this work is to test and model nonlinearities in the Taylor rule type exchange rate model to see whether a robust Taylor rule exchange rate forecasting model exists, in relation to which specifications are most appropriate (i.e. chosen transition variables) and whether allowing exchange rates to deviate from Taylor-

[53] This refers to the Meese and Rogoff (1983) finding that exchange rate models forecast no better than the random walk.

type rules improves the overall fit and forecasting ability of the model. To exploit non-linear dependencies, we apply the STR (smooth transition regression) family of models, and test several potentially important transition variables in order to capture possible nonlinearities.

The STR models were originally applied to the nonlinearity over the business cycle by Terasvirta and Anderson (1992). Over recent years, it has been widely applied to many exchange rate studies including purchasing power parity, monetary models and the theory of UIRP (Dumas, 1992; Michael et al., 1997; Baillie and Kiliç, 2006). These studies examine the possibility of nonlinearity from different perspectives but are consistent in finding the relationship between the exchange rate and the economic fundamentals is nonlinear. The STR model has been chosen over other alternative nonlinear models such as the Markov switching regime model and threshold autoregressive model in this study. This is due to a more realistic representation of the STR family models by allowing a smooth and gradual transition from one regime to another, rather than sudden jumps between regimes.

This paper contributes to the existing literature on exchange rates in several respects. Firstly, we contribute to the existing literature by extending the recent studies of the linear Taylor type exchange rate model to the nonlinear case. Our theoretical background for this study is the Molodtsova and Papell (2009) model of the exchange rate. The STR type of nonlinear econometric modelling is used to exploit the nonlinear dependencies. Unlike other works, we document and compare results from different models related to a large number of macroeconomic variables including the real exchange rate, output gap, inflation rate difference, interest rate difference, wealth effect and a measure of exchange rate volatility. The decision with regard to the best transition variable is based on both model specification and diagnostic testing. Moreover, unlike other studies which have chosen the nonlinear model in advance (e.g. Beckmann and Wilde, 2013), we identify the presence of nonlinearity and select the STR specification by linearity tests. Further, we extended the analysis to include the forecasting performance of the nonlinear STR type exchange rate models. We then investigate whether the STR type Taylor rule exchange rate models have better forecasting performance than the random walk model and the linear Taylor type model. Also, compared to the existing literature, this study covers a longer period by using data from 1970 to 2008. The results from estimation and forecasting of the nonlinear smooth transition regression model are encouraging. Firstly, we found strong evidence supporting the nonlinear relationship between the exchange rate and economic variables. Moreover, the STR models of exchange rate substantially outperform both the random walk and the linear Taylor rule model in forecasting the exchange rate.

The structure of this chapter is as follows, Section 2 gives the reasons for the potential existence of nonlinearities in the Taylor rule and exchange rate models. Section 3 introduces the STR model and outlines the specification, estimation and evaluation approaches. In section 4, we estimate several models and compare their in-sample fit and out-of-sample forecasting performance. The main conclusions are drawn in the final section.

## 6.2 Literature Reviews

The approach pursued in this chapter connects two recently developed strands of literature. Firstly, recent literature points to the possibility that the policy reaction function implied by the Taylor rule is nonlinear. Secondly, nonlinear models have been proven to be successful in explaining the failure of UIRP in the exchange rate literature.

### 6.2.1 Non-linearities in the Taylor rule

Since the establishment of the Taylor rule by Taylor (1993), a large number of authors have been using this simple linear relationship in studying monetary policy. Various results show that the actual pattern of the policy rate follows closely to this rule across various specifications and different countries[54]. However, the very recent studies have started to argue that this simple linear rule may not be able to capture the complexities in conducting monetary policy. In particular, the assumption of a linear aggregate supply function in the traditional Taylor rule may not be the case and the central bank could have asymmetric preferences. Therefore, a non-linear specifications of the Taylor rule could be better in explaining the monetary policy reaction functions of the central banks (e.g. Qin and Enders, 2008; Martin and Milas, 2004; Schaling, 2004). Previous studies have classified these asymmetries or nonlinearities in the analysis of monetary policy into several categories. These are known as asymmetry in the central bank's preferences, nonlinearities in the Phillips Curve or the interaction of both. The detail for each is discussed in the following subsection.

#### *Asymmetric central bank preference*

One of the main causes of nonlinearity in the reaction functions is asymmetric central bank preferences (e.g. Surico, 2004; Nobay and Peel, 2003; Martin and Milas, 2004; Petersen, 2007 among others.). This happens when central banks assign different weights to positive and negative output gaps and/or deviations of inflation from its target. For example, if the central bank is concerned more about the overshooting of inflation from its target and a negative output gap, it might react more strongly to a positive inflation gap or negative output gap than an equal sized negative inflation gap or positive output gap.[55] In this case, a linear Taylor rule will not reflect the actual interest rate setting behavior of the central bank. However, despite its intuitive appeal, only a few studies have tried to identify the relevance of this approach.

[54] For example, Clarida, Gali and Gertler (1998, 1999).

[55] Cukierman and Muscatelli (2008) named them as inflation-avoidance preference (IAP) and recession-avoidance preference (RAP), respectively.

Nobay and Peel (2003) demonstrate the implications of a central bank adopting an asymmetric objective function. Furthermore, Surico (2004), Surico (2007), Ruge-Murcia (2003), Robert Nobay and Peel (2003) and  Dolado et al. (2004) provide empirical evidence that asymmetric central bank preferences provides an explanation for why the policy rate adjusts in a nonlinear way to inflation and output gaps. In particular, Surico (2004, 2007) and Dolado et al. (2004) focus on US monetary policy and Ruge-Murcia (2003) use data from OECD economies. However, the nature of the non-linearity differs across studies and depends on the model and data used (Kim and Seo, 2006).

Martin and Milas (2004) examine the behavior of the Bank of England monetary policy after 1992, which is the period after the policy of inflation targeting was introduced. They use a nonlinear quadratic logistic STR model (LSTR) and assume that the monetary policy rule is generated by a Taylor rule. By assigning different weights to regimes, they find evidence of nonlinearities in the conduct of monetary policy. In particular, the nonlinear policy rule dominates a linear Taylor rule over the period 1992 to 2000. Similar results have been found by Taylor and Davradakis (2006) using a simple threshold autoregressive model over the period 1992-2003 based on UK data.

Petersen (2007) employs a simple smooth transition regression model to study the linearity of the Taylor rule. They focus on the monetary policy of the Federal Reserve and found evidence of nonlinearity in the relationship between the federal funds rate, output gap and inflation rate from 1985 to 2005: the Federal Reserve began to adjust its policy rule and respond more strongly to inflation once inflation approached a certain threshold. However, in this paper, they employed a simple Taylor rule with the interest rate adjusting to the inflation and output gap only.

Qin and Enders (2008) extend the study of Petersen (2007) by investigating the non-linearity over different forms of the Taylor rule, using the U.S. real-time data[56], they studied both the in-sample and the out-of-sample properties of a number of linear and nonlinear Taylor rules specifications. However, their results were inconsistent with Petersen's (2007): although the in-sample measure provides evidence of nonlinearity during certain time periods (i.e.1975:Q3-1995:Q4), however the results of out-of-sample forecasting support the linear autoregressive interest rate models.

All the above have focused on one specific country. Later, some studies investigated this in other economies. Cukierman and Muscatelli (2008) study the nonlinearity of the Taylor rule for the U.S. and UK. They assume asymmetric central bank preferences on inflation and the output gap and use STR type models. Their results show evidence of nonlinearity in the U.S. and U.K. Taylor rule during the period 1979-2005. Markov and De Porres (2011) build on the previous literature by testing the nonlinearity of more flexible Taylor rule specifications over 8 OECD countries. Results from both in-sample estimation and out-of-sample forecasting point to strong evidence of nonlinearity in the Taylor rule.

***Nonlinearities in the Phillip Curve***

Another potential rationale for nonlinearities in the Taylor rule comes from the so-called nonlinear Phillips curve (e.g. Schaling, 2004; Dolado et al., 2005; Nobay and Peel, 2000). This strand of the literature recognises the fact that the relationship between output and inflation is nonlinear.[57] For example, over different phases of the business cycle, inflation and the output gap are inherently nonlinear: output exhibits short and sharp recessions but long and smooth recoveries, whereas inflation

[56] Real time data here refers to the data available to the Fed when they set the interest rate (i.e. information from the Federal Reserve Greenbook).

[57] The nonlinear Phillip curve has been discussed by Laxton et al. (1995), Gerlach, S. (2000), Laxton et al. (1995), Bean, C. (1996) and Clark et al. (1996).

increases more rapidly than it decreases. In other word, inflation increase more rapidly than increase in output for a rise in aggregate demand. Such an environment would require policy makers to respond differently during recessions and expansions. If this is the case, then the optimal feedback rule relating interest rates to output and inflation should also be nonlinear (Petersen, 2007).

In this area of research, Kaufmann (2002), Altavilla and Landolfo (2005) and Assenmacher-Wesche (2006) apply Markov-Switching models and find evidence of asymmetries in the monetary authorities' adjustment over the course of the business cycle. Similar research has also been carried by Nobay and Peel (2000). They have re-examined the performance of optimal interest rate rules in case the relationship between inflation and the output gap (i.e. Phillips Curve) is nonlinear. Both of their results demonstrate that a nonlinear inflation-output trade-off will impart a bias to inflation when a linear rule is used. Further research carried out by Schaling (2004) and Dolado et al. (2005) shows that, in such cases, the optimal policy rule becomes also nonlinear.

In particular, Schaling (2004) has employed dynamic optimization techniques to examine the inflation-forecast targeting of a convex Phillips curve. When the Phillips curve is convex, the co-movement between inflation and the level of output is positive. This convexity in the inflation and output relationship implies that the optimal monetary policy rule is asymmetric. In such a case, the interest rate is a nonlinear function of the deviation of inflation from its target and the output gap.

Dolado et al. (2005) have extended the work of Schaling (2004) by re-examining the effect of a convex Phillip Curve on interest rate setting across countries based on the Taylor rule model. They investigated the implications of a nonlinear Phillips curve on the interest rate setting behavior of three European countries, the U.S. Federal Reserve and the European Central Bank. Their results have confirmed those derived by Schaling (2004) and showed evidence of nonlinear policy rules for four European central banks.

### 6.2.2 Non-linearities in Exchange rate models

The Taylor rule based exchange rate models are derived by assuming the expected rate of exchange rate change is proportional to the interest rate differential.[58] In other words, although there is some debate over the sign in these models, the expected exchange rate change is linked to the Taylor rule by assuming UIRP. Most previous empirical research on UIRP has generally relied on the linear framework. However, many studies report results that are unable to support the UIRP hypothesis (e.g. Carlson, 1998; Sarno and Taylor, 2003). To provide an explanation for the failure of the theory, many studies have tried to emphasise a possible nonlinear relationship between exchange rate movements and interest rate differentials. The nonlinear UIRP has been explained by a number of theories in international finance, including the effect of central bank intervention, transaction costs, speculative restrictions and heterogeneous trading behavior.

***Central bank intervention***

One of the main reasons for the forward premium anomaly is central bank intervention (McCallum's, 1994; Anker, 1999; Chinn and Meredith, 2004).[59] According to the Krugman (1993) specification, the UIRP holds if market participants are fully rational and have common and credible knowledge of any central bank intervention. However, if the central bank's intervention takes place contrary to agents' expectations, it is going to create instantaneous but unexpected shifts in the stochastic process that governs the interest rate differential. Therefore, failure to correctly anticipate these sporadic shifts will lead to occasional UIRP violations. Mark and Moh (2002) argue that, in the presence of central bank

[58] The detailed discussion on the derivation of Taylor Rule Exchange Rate model is presented in section 2.6.

[59] This is when the change in the spot exchange rate is inversely related to the premium of the forward rate over the spot rate.

intervention, nonlinear adjustment of the exchange rate to the interest rate differential may offer a solution to the forward premium anomaly.

The idea that the effect of monetary policy could result in a negative relationship between exchange rate changes and interest rate differentials was pioneered by McCallum (1994). By using a two equation framework combining the UIRP relationship with a monetary policy reaction function, he found that the simultaneous interaction between the monetary authorities smoothing of interest rate movements and resisting rapid change in the exchange rate can explain the failure of UIRP.[60]

Later on, Chinn and Meredith (2004) extended the framework of McCallum (1994) by including output and inflation into the monetary policy reaction function. In other words, instead of the exchange-rate targeting assumption employed in McCallum's (1994) model, Chinn and Meredith (2004) allow interest rates to change in response to movements in output and inflation. Their Results from stochastic simulations are consistent with McCallum's (1994) finding. The failure of UIRP in the short run is caused by the interaction of foreign exchange market shocks and monetary policy reactions. Results from the above suggest that a smooth transition in the UIRP parameter is required to account for the effect of central bank intervention.

Mark and Moh (2002) and Mark and Moh (2007) show that a continuous-time model, where the exchange rate is a nonlinear function of interest rate differentials, offers a solution to the forward premium anomaly caused by central bank intervention. In particular, Mark and Moh (2007) investigate the violation of UIRP from the perspective of unanticipated central bank intervention in the foreign exchange market. They emphasised the surprise element of the interventions which market participants cannot anticipate. A continuous-time stochastic model is employed where central bank intervention is reflected by adjusting the interest rate differential within a band. Simulation results show that central bank interventions lead to

[60] Resisting change in exchange rate is also know as' leaning against the wind'.

deviations from UIRP. Moreover, using a nonlinear function of the exchange rate with respect to interest rate differentials may offer a solution to the forward bias puzzle.

Moreover, Reitz et al. (2011) analyse the effect of central bank intervention in the Australian-U.S. foreign exchange market using a nonlinear smooth transition model. Results indicate policy makers' decisions have a nonlinear influence on the exchange rate in the sense that mean reversion increases with the degree of exchange rate misalignment.

***Transaction costs***

The nonlinear specification of the exchange rate can also be explained by models incorporating transaction costs.[61] Theoretical support for this theory can be found in the works of Dumas (1992) and Sercu et al. (1995). The general idea is that, transaction costs normally create a band of inactivity within which arbitrage is non-profitable. As a result, the real exchange rate deviation from purchasing power parity (PPP) is not corrected inside the band, and the real exchange rate can move in any direction freely according to random shocks to the economy. However, when the exchange rate moves outside the transaction band, deviations from PPP will follow a mean-reverting process with the exchange rate moving back to the edge of the band due to arbitrage. If this is the case, then nominal exchange rates will depend nonlinearly on their fundamentals.

Baldwin (1990) developed a partial equilibrium model of the exchange rate and considered a case where there are only two investment possibilities in the world: home and foreign currency dominated assets. The risk neutral foreign exchange traders face a choice of investing in one or other of these assets with a small

[61] Transaction costs can be broadly defined to include transportation costs, tariffs and nontariff barriers, as well as any other costs that agents incur in international trade (Obstfeld, M. and K. Rogoff, 2001).

transaction cost of moving between them. After finding the optimal arbitrage strategy, he shows that small transaction costs and uncertainty will produce a band, known as the hysteresis band. Within this hysteresis band, no trade will take place and small interest rate differentials have no effect on the expected spot returns. Only when interest rate differentials lie outside the band, does UIRP hold with the expected change in the exchange rate affected by interest rate differentials. Dumas (1992) modelled the dynamics of the real exchange rate using a general equilibrium model. He showed the nominal exchange rate depends nonlinearly on the fundamentals. Moreover, the speed of adjustment to parity is a function of the size of the deviation from parity.

Motivated by theoretical models, Obstfeld and Taylor (1997) and Michael et al. (1997) have provided empirical evidence of nonlinear behavior in purchasing power parity (PPP) based on the U.S. dollar real exchange rate. In particular, Obstfeld and Taylor (1997) employed a band-TAR model and examined the nonlinear real exchange rate based on a large number of consumer price indices. Michael et al. (1997) applied the ESTAR model and investigated the adjustment process for PPP based on a small number of Sterling and U.S. dollar exchange rates. Both studies recognize that transaction costs prevent arbitrage from correcting the real exchange rate within the transection band; outside the band, arbitrage forced the real exchange rate to move back to the edge of the band. Sarantis (1999) has suggested that this misspecification can be avoided by applying the STAR models directly to the real exchange rate.

More recently, Sercu and Wu (2000) and Sarno et al. (2006) apply the STAR model to some U.S. dollar exchange rates. Their results provided empirical evidence of nonlinearity in the spot-forward exchange rate relationship. Deviations from the UIRP suggest the presence of nonlinearity due to the presence of transaction costs and limits to speculation. López-Suárez and Rodríguez-López (2011) construct a nonlinear smooth transition error correction model for studying the nonlinear predictability of nominal exchange rates under the assumption that the nonlinearity is due to transaction costs. Using a panel quarterly data set from 1973 to 2009 based on 19 countries, they found that nonlinear models can produce better exchange rate predictability.

***Limits to speculation***

The hypothesis of limits to speculation can also be used to interpret possible nonlinear relationships between exchange rate changes and forward exchange rate premiums. Among this line of research, Lyons (2001), Sarno et al. (2006) and Baillie and Kilic (2006) have given various explanations for the nonlinear behavior of deviations from UIRP under the assumption of speculative restrictions. Those theoretical and empirical studies on the failure of UIRP lead to a strong suggestion of a nonlinear relationship between spot returns and the forward premium and therefore a strong suggestion of a nonlinear Taylor rule exchange rate model.

The limits to speculation hypothesis proposal is based on the idea that financial institutions only take up a currency trading strategy if this strategy's expected return per unit of risk (i.e. Sharpe ratio) is higher than the one implied by alternative trading strategies, such as, for example, a simple buy-and-hold equity strategy (see Lyons, 2001, Ch.7, pp. 209-220).

Lyons (2001) analysed bias-trading strategies based on equally weighted carry trade portfolios of six U.S. dollar based exchange rates and found that it only worked when the currency strategy had a Sharpe ratio higher than the minimum threshold level of 0.5. This is the annually based average Sharpe ratio for a buy-and-hold equity strategy (i.e. not concern with short term price movement) for the US over the last 50 years, where the deviation from UIRP will be considered as an arbitrage opportunity by traders.[62] This argument effectively defines a band of inaction where

[62] Based on an interview with proprietary traders at banks and hedge funds, Lyons (2001) reports trader's interest would be limited for strategies with Sharpe ratios lower than 0.4 (after approximating transaction costs) and thus support for his hypothesis.

the forward bias does not attract speculative capital and financial institutions would have no incentive to take up the currency strategy since a buy-and-hold equity strategy would have a higher return per unit of risk. Within this band, UIRP does not hold. The expected deviation from the UIRP does not imply any opportunity for profit and it will persist until it generates Sharpe ratios that are large enough to attract speculative capital away from alternative trading strategies (Lyons, 2001).

Inspired by the limited to speculation hypothesis, Sarno et al. (2006) and Baillie and Kilic (2006) apply the smooth transition regression (STR) model to study the exchange rate. Both studies find strong evidence of nonlinearities in the UIRP based on the theory of transaction costs and limits to speculation. In particular, Sarno et al. (2006) employ an exponential smooth transition regression (ESTR) model to study the major U.S. dollar exchange rates. They used the deviation from the UIRP as the transition variable. Their results confirm the finding of Lyons (2001) by indicating a threshold level for the Sharpe Ratio of 0.4. Baillie and Kilic (2006) apply logistic smooth transition regression (LSTR) models to study the relationship between exchange rate changes and lagged forward premium, in their study the lagged forward premium has been used as the transition variable.

***Heterogeneous Traders***

In addition to the above factors, heterogeneity in agents' opinions on the equilibrium level of the nominal exchange rate may also generate nonlinearity. The notion of heterogeneous agents refer to the idea that people usually have different and changing beliefs about the behavior of the exchange rate. These different and changing beliefs will thereby introduce nonlinear features into the dynamics of the exchange rate. As argued by Sarantis (1999, p.28): "Heterogeneity of participants in the foreign exchange market is often cited as the major source of nonlinearities in the exchange rate process."

Sarantis (1999) tested for nonlinearity in the real exchange rate based on a smooth transition autoregressive (STAR) model by assuming the form of non-linearity is driven by the presence of heterogeneous investors. Their tests rejected the linearity hypothesis and found evidence in support of the STAR model in improving the forecasts compared to a random walk model and the alternative nonlinear Markov regime-switching model in terms of the RMSE criterion. He further emphasised that each switching between regimes is coming from diversities in investors' beliefs, learning speeds and investment horizons. This is similar to the conclusion of Peters (1994) and Guillaume et al. (1997), who suggested that heterogeneity in the objectives of investors comes from different investment horizons, geographical locations, various types of risk profiles and institutional constraints.

Taylor et al. (2001) considered the results from Terasvirta (1994), Dumas (1994) and Bertola and Caballero (1990) and suggested that non-synchronous adjustment by heterogeneous agents is likely to lead to smooth regime switching, rather than discrete switching. Kilian and Taylor (2003) confirmed the results of Taylor et al. (2001) by finding evidence of a nonlinear relationship between the nominal exchange rate and its economic fundamentals. They show this nonlinear behavior of the exchange rate results from heterogeneous traders and can be reasonably well described by an exponential smooth threshold autoregressive (ESTAR) model. Furthermore, they made a distinction between noise traders and rational speculators and argued that the real exchange rate is driven by noise traders when it moves close to equilibrium.[63] However, as exchange rates move away from equilibrium, rational speculators take stronger positions. Therefore, exchange rates can be considered as a random walk for small deviations from equilibrium and as deviations from equilibrium get large, mean reversion eventually occurs.

[63] According to Hommes, C.H. (2006), noise traders are traders who simply trade by non-fundamental considerations in foreign exchange market. Rational speculators are investors who form fully rational expectations about foreign exchange holding return.

## 6.3 Nonlinear adjustment in the Taylor rule exchange rate model

### 6.3.1 Theoretical reasons for the Selection of nonlinear models

Classified in terms of the behaviour of the regime switching, there are two types of nonlinear time series models which can be used to explain the non-linear behaviour of the exchange rate: the Markov regime switching model and the threshold model. They are similar in a way in that both classes of models involve defining different states of regimes and allowing economic variables to behave differently within these different regimes. However, the Markov switching model (see Hamilton, 1989) assumes that changes in regime are defined by an unobserved state variable with its transition probabilities described by a Markov Chain process. But the threshold models assume the shift from one regime to another is determined by an observable variable, in other words, the threshold model allows regime switching to be a function of a past value of the time series itself (Potter, 1999).[64] In order to capture the nonlinear behaviour of the exchange rate transmission, this study chooses the family of smooth transition regression (STR) models.[65]

The precursor of the STR model is the threshold autoregressive (TAR) model introduced by Tong (1978) and Tong and Lim (1980). The TAR model can be considered as a piecewise linear autoregressive models, which allows the linear relationship to differ in different regimes according to an exogenous threshold value.[66] For example, once the series crosses a certain threshold, it immediately transits to a long run level. This model is capable of explaining threshold behavior but there is one shortcoming: the switch between regimes occurs abruptly at a specific value of the threshold variable. Granger and Terasvirta (1993b) introduce a more general class of state-dependent nonlinear time series models named STAR

[64] This is also known as the self-exciting threshold models.

[65] STAR model is considered as a univariate special case of the general STR model.

[66] The model is a self-exciting threshold autoregressive model if the regime is determined by the past value of the time series.

models. In these models, the fixed thresholds in the TAR model are replaced by a smooth function to allow a more gradual transition from one regime to another.

The STR models are more flexible and more suitable for analysing the nonlinear adjustment in the Taylor rule type exchange rate approach. Firstly, unlike Markov regime switching models and TAR models which assume a discrete switching between regimes, the STR models assume a smooth transition between regimes depending on the transition variable. In foreign exchange markets with a large number of investors, a smooth transition between regimes is more preferable and appropriate as investors do not adjust simultaneously due to heterogeneous beliefs, different learning speeds and investment horizons (Sarantis, 1999). Moreover, the existence of transaction costs makes investors adjust their portfolios infrequently and implies a gradual shift in the regime is more suitable (Lyons, 2001). Secondly, our Taylor rule exchange rate model assumes that endogenous monetary policy exists in the Taylor rule based exchange rate model. As argued by Petersen (2007), unlike Markov-switching models, the STR model allows for endogenous regime switching and therefore is able to provide economic intuition for the nonlinear behavior of the exchange rate. Another important feature of the STR models is that they nest linear regression models. Therefore, we can develop Lagrange multiplier (LM) tests for testing the null of linearity fitting any type of nonlinear model. The choice of selection between the alternative STR specifications can also be made from the results of the LM tests (Granger and Terasvirta, 1993a).

In this study, STR models are employed in studying the nonlinear behaviour of the Taylor rule derived exchange rate models. We now assess how changes in central bank monetary policy rules affect the nonlinear behaviour of the Taylor rule exchange rate.

### 6.3.2 STR models

Following the work of Teräsvirta (1996), the STR model assumes there are at least two regimes with different sets of coefficients and a transition variable which determines the movements across the regime.

A standard two regime STR model has the following specification:

$$y_t = \boldsymbol{\phi} \boldsymbol{z}_t + \boldsymbol{\theta} \boldsymbol{z}_t \cdot G(s_t;\ \gamma, c) + u_t \tag{6-1}$$

where $\boldsymbol{z}_t$ is a vector of explanatory variables including a constant, some explanatory variables and, possibly some lagged values of $y_t$. $\boldsymbol{\phi}$ and $\boldsymbol{\theta}$ representing parameter vectors for the linear and nonlinear parts of the model respectively. $u_t$ denotes a sequence of disturbance terms which assumed *i.i.d.* with zero mean and constant $\sigma$.

$G(s_t;\ \gamma, c)$ is the transition function assumed to be continuous and bounded between 0 and 1, $s_t$ is the transition variable, $\gamma$ is the transition parameter, also known as the speed of transition, it determine how quickly the transition between regimes occurs and is restricted by $\gamma > 0$. $c$ denotes the particular threshold level and corresponds to the value of the transition variable where the transition takes place. Both $\gamma$ and $c$ are estimated by the model. The transition variable $s_t$ can be an element or a linear combination of $\boldsymbol{z}_t$ or a linear deterministic trend.

There are two alternative functional forms for the transition function:

- Logistic Function:

$$G(s_t;\ \gamma, c) = \frac{1}{1 + \exp[-\gamma(s_t - c)]} \tag{6-2}$$

- Exponential Function:

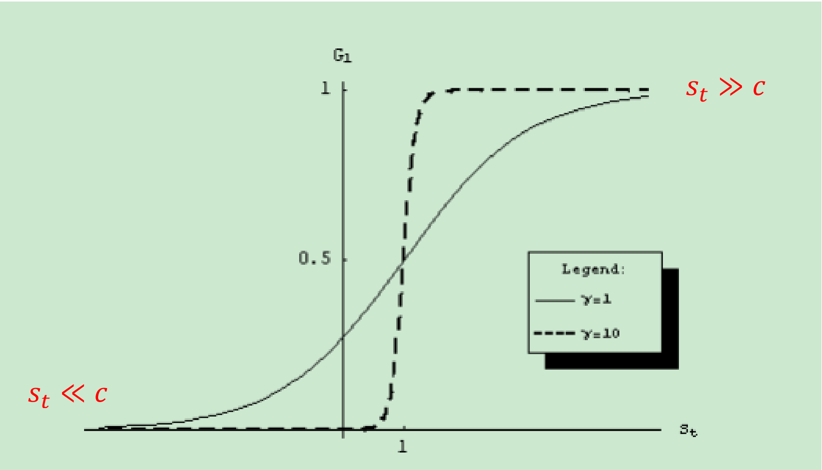
$$G(s_t;\ \gamma, c) = 1 - exp\left[-\gamma(s_t - c)^2\right] \tag{6-3}$$

Equation (6-1) combined with transition function (6-2) jointly define the logistic STR (LSTR) model. Equation (6-1) with transition function (6-3) formed an exponential STR (ESTR) model. Different functional forms of $G(s_t;\,\gamma, c)$ correspond to different types of exchange rate switching behaviour.

### *Logistic Smooth Transition Regression (LSTR)*

For the logistic STR model, the transition function is a monotonically increasing function of $s_t$. Therefore, the LSTR models describe relationships that change according to the level of the threshold variable. Given that $G(s_t;\,\gamma, c)$ is continuous and bounded between zero and one, the combined nonlinear coefficients $\phi + \theta \cdot G(s_t;\,\gamma, c)$ will change monotonically from $\phi$ to $(\phi + \theta)$ according to different values of $s_t$. When $s_t - c \to +\infty$, $G(s_t;\,\gamma, c) \to 1$ and coefficients become $\phi + \theta$; when $s_t - c \to -\infty$, $G(s_t;\,\gamma, c) \to 0$ and coefficients become $\phi$. In the case that $s_t = c$, $G(s_t;\,\gamma, c) = 0.5$ and the coefficients become $\phi + 0.5\,\theta$. As shown in Figure 6-1, where the LSTR model is describing asymmetric behavior.

**Figure 6-1 LSTR transition function with $c = 1$**



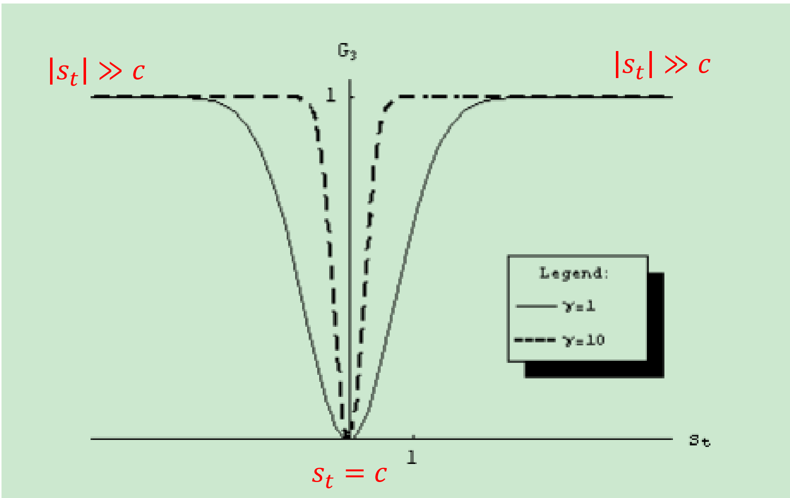

*Notes:* from 'Nonlinear econometric models: The smooth transition regression approach'. (Kavkler et al., 2007, p.6).

It is also worth noting that the STR model approaches a linear model or a nonlinear threshold regression model as a special case. Dijk et al. (2002) point out, that when $\gamma \to 0$ , the transition function $G(s_t;\, \gamma, c) = 0.5$ and the LSTR model simplifies to a linear model. However, when $\gamma \to \infty$, the change of $G(s_t;\, \gamma, c)$ becomes almost instantaneous at $s_t = c$. Therefore, LSTR models converge to a two regime threshold regression model with the extreme regimes $y_t = \phi \boldsymbol{z}_t + u_t$ (i.e. when $s_t \leq c$) and $y_t = (\phi + \theta)\boldsymbol{z}_t + u_t$ (i.e. when $s_t > c$).

### *Exponential Smooth Transition Regression Models (ESTR)*

In contrast to the logistic function, the exponential function is symmetric and U-shaped around $c$. It describes dynamic behavior which is the same for high values of transition variables as it is for its low values. However, as the variable gets close to the threshold level, the local dynamic behavior varies.

**Figure 6-2 ESTR transition function with $c = 0$**




*Note:* from 'Nonlinear econometric models: The smooth transition regression approach'. (Kavkler et al., 2007, p.7).

The transition function $G(s_t;\ \gamma, c) \to 1$ both as $s_t - c \to -\infty$ and $s_t - c \to +\infty$ and the coefficient of the model becomes $(\phi + \theta)$. In the case of $s_t = c$, $G(s_t;\ \gamma, c) = 0$ and the coefficients become $\phi$.

One drawback of the ESTR model is that it does not nest a threshold model as a special case. For either $\gamma \to 0$ and $\gamma \to \infty$, the function approaches a constant (i.e. 0 and 1 respectively) and the model becomes linear.

## 6.4 The Modelling Strategy for STR Models

In developing the analysis of possible nonlinearity in the Taylor rule exchange rate models, we will use the procedure discussed in Granger and Terasvirta (1993a) and Teräsvirta (1994, 1996). This modelling cycle for STR models consists of three steps: specification, estimation and evaluation.

### 6.4.1 Specification

As a starting point, an adequate linear representation must be specified. It is convenient to recall the model from the previous empirical chapter, our Taylor rule exchange rate model taking the following form:

$$\Delta s_{t+1} = \alpha_m + \beta_m X_{m,t} + \eta_{m,t+1} \quad (6\text{-}4)$$

where $\Delta s_{t+1}$ is the change in the log of the nominal exchange rate determined as the domestic price of foreign currency; $X(m,t)$ is a vector of the different economic explanatory variables. We then select the most comprehensive restricted model for model estimation: [67]

[67] The Wald-test in chapter 4 has proven that the restriction hold for these models.

UK & Australia: Model 3:

$$X_{3,t} \equiv [\ \pi_t - \tilde{\pi}_t \quad y_t - \tilde{y}_t \quad \tilde{q}_t \quad i_{t-1} - \tilde{\imath}_{t-1} \quad w_t(s) - \widetilde{w}_t(s)\ ]$$

Sweden: Model 4:

$$X_{4,t} \equiv [\ \pi_t - \tilde{\pi}_t \quad y_t - \tilde{y}_t \quad \tilde{q}_t \quad i_{t-1} - \tilde{\imath}_{t-1} \quad w_t(h) - \widetilde{w}_t(h)\ ]$$

In order to facilitate the comparison across countries and model specifications, I have not removed any of these variables from the models even when the coefficients were insignificant.

The Taylor rule STR model takes the following form:

$$\Delta s_{t+1} = \phi \boldsymbol{z}_t + \theta \boldsymbol{z}_t \cdot G(s_t;\ \gamma, c) + \varepsilon_t \tag{6-5}$$

here $G(..)$ is the transition function; $z_t$ is the vector of regressors in the above models. The vector $\phi = \left(\alpha_0, \beta_\pi, \beta_y, \beta_i, \beta_w, \beta_q\right)$ and $\theta = \left(\alpha_0^*, \beta_\pi^*, \beta_y^*, \beta_i^*, \beta_w^*, \beta_q^*\right)$ contains parameters from the linear and nonlinear sections of the model.

The second step involves: selecting the appropriate transition variable in the STR model, testing of nonlinearity and deciding the most suitable form of the transition function.

### ***The Transition Variable Selection Process***

The application of the linearity and model selection tests requires a prior selection of a set of variables to be included in the transition regression. As suggested by the literature review in section 6.2, nonlinearity in the Taylor rule exchange rate model may come from nonlinearity in either the Taylor rule or exchange rate. Therefore, the hypothesis of nonlinearity in the Taylor type exchange rate can be tested simply by evaluating the functional form of the interest rate reaction function and exchange rate. In this study, six different transition variables are chosen for the nonlinear estimation. These are the output gap, interest rate differential, inflation differential, asset price differential, real exchange rate and exchange rate volatility. Apart from exchange rate volatility, all the above are important determinants in the simple linear Taylor rule exchange rate model.

Some of them have been previously used as transition variables in nonlinear policy rule studies. For example, the output gap and inflation have been widely used as transition variables in nonlinear Taylor rule studies based on the theory of asymmetric central bank preferences and nonlinear Phillip Curves. Studies by Martin and Milas (2004), Petersen (2007) and Dolado et al. (2005) among others find that these are important transition variables in identifying nonlinearity in the Taylor rule. Some assume that the central banks rely on all available information and using a forward looking Taylor rule with interest rate smoothing. For example, Brüggemann and Riedel (2011) find the logistic STR model with lagged interest rates as the transition variable were the preferred model specification in studying the nonlinear interest rate reaction functions. The interest rate differential has also been used in many exchange rate studies as a transition variable (e.g. Mark and Moh, 2002 and Mark and Moh, 2007). These studied are based on the theory of central bank intervention as discussed in the literature review in section 6.2.

The use of the real exchange rate as a transition variable has been discussed in the literature on nonlinearities in exchange rates. Sarantis (1999) investigates nonlinearities in the real exchange rate in the STAR family of models and argued the major source for this nonlinearity is heterogeneity in participants' opinions.[68] The wealth effect through asset price, though has not been studied in the context of nonlinear exchange rate models before, Castro (2008) has discussed the importance of asset prices (i.e. house price, stock price) in the conduct of monetary policy and showed using the European Central Bank as an example that central banks may continue to consider other information such as change in asset prices even after

[68] More detail about heterogeneous participants is discussed in the literature in section 6.2.2.

linearities had been controlled. This gives a motivation for investigating the possibility of nonlinearities in the exchange rate due to these wealth effects.

The final selected transition variable in this study is exchange rate volatility. This is used to study how the exchange rates derived from the Taylor rule are related to the market risk by including the risk premium in the nonlinear model. This is motivated by the fact that many studies have shown risk premium can lead to the failure of UIRP condition. In measuring exchange rate volatility, we used the conditional volatility series produced from a generalized autoregressive conditional heteroscedasticity (i.e. GARCH (1, 1)) framework. Previous studies have exploited the fact that one of the most important explanations for the failure of UIRP is the presence of a foreign exchange risk premium (e.g. Lewis, 1995; MacDonald, 2000). This is often related to the theory of the carry trade and the limits to speculation hypothesis.[69] Ichiue and Koyama (2011), for example, employed a regime switching model to investigate how exchange rate volatility is related to the failure of UIRP. They show that the failure of UIRP is due to it only holding in regimes of low exchange rate volatility. This may be because a higher Sharpe ratio attracts investors into the carry trade. Baillie and Chang (2011) confirm the result of Ichiue and Koyama (2011) by employing a LSTR model. They analyse the effects of the carry trade motived by the limits to speculation hypothesis and they have shown that UIRP is more likely to hold in regimes with high exchange rate volatility.

Since we have no way of telling which of these variables should be taken as the transition variable, we use the method in Teräsvirta (1996), by testing the null hypothesis of linearity for each of the possible transition variables in turn.

[69] The Carry trade is an investment strategy that exploits the failure of UIRP by borrowing in low-interest currencies and then investing in high-interest rate currencies.

### *Test for nonlinearity*

After deciding on the predetermined transition variable, the null hypothesis of linearity is tested against a STR model with these predetermined transition variables. The test is repeated for each of the potential transition variables. When the null hypothesis of linearity is rejected in favour of STR nonlinearity, the transition variable will be selected as the best possible candidate. Upon deciding on the possible transition variable, we have to make a final decision on the appropriate form of the transition function to be taken.

From the STR specification in section 6.3.2, we note that when the speed of transition, $\gamma$, approaches zero, both LSTR and ESTR models reduce to a linear model. Therefore, we can test the linearity of a regression model by simply testing if the speed parameter in the transition function equals zero. Teräsvirta (1994) and Teräsvirta (1996) suggest approximating the transition function with a third order Taylor series expansion around the null hypothesis $\gamma = 0$. This will generate the following auxiliary regression for testing the linearity:

$$\Delta s_{t+1} = \delta_0' \boldsymbol{z}_t + \sum_{j=1}^{3} \delta_j' \tilde{\boldsymbol{z}}_t s_t^j + \varepsilon_t^* \tag{6-6}$$

where $\tilde{\boldsymbol{z}}_t$ is the vector of variables in $\boldsymbol{z}_t$ without the constant; $s_t$ is one of the elements of $\boldsymbol{z}_t$. Under the null of linearity ($H_0$): $\delta_1 = \delta_2 = \delta_3 = 0$; whilst under the alternative hypothesis, at least one $\delta_j \neq 0,\ j = 1,2,3$. As advised by Teräsvirta (1994), F-versions of the LM test statistics are employed as these have better size properties than the $\chi^2$-statistic.[70]

[70] In small or moderate sized samples, the $\chi^2$-statistic may be heavily oversized (Dijk et al. (2002)).

***Choose between LSTAR and ESTAR models***

Once linearity has been rejected, one has to choose the appropriate form of the transition function. The decision is based on testing the order of the polynomial in auxiliary regression (6-6). Granger and Teräsvirta (1993a) and Teräsvirta (1994) proposed the following sequence of null hypotheses:

$$H_{03}:\ \delta_3 = 0 \tag{6-7}$$

$$H_{02}:\ \delta_2 = 0\ given\ \delta_3 = 0 \tag{6-8}$$

$$H_{01}:\ \delta_1 = 0\ given\ \delta_3 = 0, \delta_2 = 0 \tag{6-9}$$

According to Teräsvirta (1994), the decision rules for choosing between LSTR and ESTR models are the following: We comparing the significance level of the three F-tests, if the p-value of the test corresponding to $H_{02}$ is the smallest among the three, select an ESTAR model; otherwise a LSTAR model is chosen as the appropriate model.

### 6.4.2 Estimation

Once the transition variable and the corresponding functional form have been selected, the parameters of the STR model are estimated in the next stage of the modelling cycle.

The specific STR models are estimated using the non-linear least squares (NLLS) technique. As discussed by Dijk et al. (2002), NLLS is equivalent to the maximum likelihood method under the assumption of normally distributed errors.

As a starting point, we follow the method suggested by Dijk et al. (2002) and construct a grid search for the parameter $\gamma$ and $c$ for the nonlinear optimization. For the estimation of parameter $\gamma$, we scale the transition function: dividing it by the standard deviation of $s_t$ (i.e. $\hat{\sigma}_s$ ) for LSTR models and by the variance estimate of

$s_t$ (i.e. $\hat{\sigma}_s{}^2$) in the case of ESTR. The purpose of standardizing the transition function is to make it easier to compare estimates of the transition parameters across different equations.[71] Hence, the transition function can be re-expressed as:

Logistic: $$G(s_t;\ \gamma, c) = \frac{1}{1 + \exp[-\gamma\ (1/\hat{\sigma}_s)(s_t - c)]} \tag{6-10}$$

Exponential: $$G(s_t;\ \gamma, c) = 1 - exp\left[-\gamma\left(1/\hat{\sigma}_s{}^2\right)(s_t - c)^2\right] \tag{6-11}$$

Based on this scaling, I have used $\gamma = 1$ as a starting point for the grid search, and set increments equal to 0.1. The grid search for location parameter $c$ is based on the 15% and 85% percentiles of the transition variable $s_t$ . The residual sum of squares is computed for each value of $\gamma$ and $c$ and the values corresponding to the minimum of that sum are taken as the starting values in the NLLS procedure. This procedure reduces the problem in NLLS estimation and the time needed for convergence of the NLLS algorithm.

### 6.4.3 Evaluation

The final stage of the cycle is to evaluate the quality of the estimated STR model. Lin and Teräsvirta (1994) and Eitrheim and Teräsvirta (1996) have developed three kinds of misspecification tests that were specially designed for evaluating the adequacy of a single equation STAR model. However, these can also be adjusted and applied to STR models. These tests are known as the LM tests for no autocorrelation, the LM test of no remaining nonlinearity and the LM test of parameter constancy. Other commonly used tests in the STR literature include the Jarque-Berra test for the

[71] This is also recommended by Granger et al. (1993a) and Teräsvirta (1994). They argued that scaling the transition variable by its own standard deviation before running empirical estimation not only speeds up the convergence but also improves the stability of the nonlinear least squares estimation algorithm.

normal distribution of the errors and the LM test of no autoregressive conditional heteroscedasticity (ARCH) in the residual. The following section gives a brief description of the first two tests, the others are performed using the same approach as in the linear case.

### *Test of no residual autocorrelation*

As argued by Eitrheim and Teräsvirta (1996), the usual Ljung and Box (1978) (LB) test for a linear model is inappropriate with a STR model. When the test is based on the estimated residual of a STR model, the asymptotic null distribution of the LB test is unknown.

The most suitable test for no residual autocorrelation in a STR model (6-5) is a Breusch-Godfrey LM test. The test procedures are derived as follows: firstly estimate equation (6-5) by NLLS and obtain a set of sample residuals $\hat{\varepsilon}_t$. Then regress $\hat{\varepsilon}_t$ on $q$ lagged residuals $\hat{\varepsilon}_{t-1}, \dots, \hat{\varepsilon}_{t-q}$ and $\nabla \mathrm{F}(\boldsymbol{z}_t;\ \hat{\tau}) = \partial F\big(\boldsymbol{z}_t;\ \hat{\theta}\big)/\partial \tau$ where

$$\mathrm{F}(\boldsymbol{z}_t;\ \tau) = \phi \boldsymbol{z}_t + \theta \boldsymbol{z}_t \cdot G(s_t;\ \gamma, c) \qquad (6\text{-}12)$$

$\tau = (\phi, \theta, \gamma, c)$; a hat indicates the relevant quantities are estimates under the null hypothesis of the serial independence of $\varepsilon_t$. Calculate the usual coefficient of determination $R^2$ for this model. Then an LM test for q-th order serial dependence in $\varepsilon_t$ can be obtained as $nR^2$. This test statistic follows a $\chi^2$ distribution with $q$ degree of freedom.

### *Test of no remaining linearity*

The test for no remaining linearity examines whether or not there exists some remaining nonlinearity in the process after the initial non-linearity is controlled for. This possibility is investigated by assuming that the additional nonlinearity is also a

STR type. Therefore, the alternative hypothesis can be expressed as equation (6-5) with two STR components instead of a single one, i.e.

$$\Delta s_{t+1} = \phi \boldsymbol{z}_t + \theta \boldsymbol{z}_t \cdot G(s_{1t};\ \gamma_1, c_1) + \psi \boldsymbol{z}_t \cdot F(s_{2t};\ \gamma_2, c_2) + u_t \qquad (6\text{-}13)$$

Where $u_t \sim iid(0\,, \sigma^2)$; $F(s_{2t};\ \gamma_2, c_2)$ is another transition function of either type (6-2) or (6-3). The process to construct the test is as follows: firstly, the model is estimated without the second nonlinear component, then the null hypothesis of $\gamma_2 = 0$ or $F = 0$ is tested against (6-13).

Similar to the logic applied in the linearity test, we replace the transition function $F(s_{2t};\ \gamma_2, c_2)$ by a third-order Taylor series approximation around $\gamma_2 = 0$, and then the corresponding auxiliary regression is used:

$$\Delta s_{t+1} = \delta_0' \boldsymbol{z}_t + \theta \boldsymbol{z}_t \cdot G(s_{1t};\ \gamma_1, c_1) + \sum_{j=1}^{3} \delta_j' \tilde{\boldsymbol{z}}_t s_{2t}^j + u_t^* \qquad (6\text{-}14)$$

The null hypothesis of no additional nonlinearity becomes $H_0$: $\delta_1 = \delta_2 = \delta_3 = 0$; $s_{2t}$ could take variables from the subset of $\boldsymbol{z}_t$ or $s_{1t}$. The resultant test statistic is constructed in the same way as in the linearity test.

***Test of parameter constancy***

The test of parameter constancy is constructed by testing the null of constant parameters against the alternative that the parameters in (6-5) change smoothly and continuously over time. The purpose of the parameter constancy test is to assess if there exists any structural change in the parameters. If the null of parameter constancy cannot be rejected, we conclude that the parameters are time invariant.
Rewriting equation (6-5) as follows:

$$\Delta s_{t+1} = \phi(t) \boldsymbol{z}_t + \theta(t) \boldsymbol{z}_t \cdot G(s_t;\ \gamma, c) + \varepsilon_t \qquad (6\text{-}15)$$

$\phi$ and $\theta$ are time-varying parameters:

$$\phi(t) = \phi + \lambda_1 H_\phi\big(t;\ \gamma_\phi, c_\phi\big) \tag{6-16}$$

$$\theta(t) = \theta + \lambda_2 H_\theta(t;\ \gamma_\theta, c_\theta) \tag{6-17}$$

where $H_\phi$ and $H_\theta$ are transition functions with $s_t = t$ ; $\varepsilon_t \sim iid(0\,, \sigma^2)$; the null hypothesis is $\gamma_\phi = \gamma_\theta = 0$.

Similar to the logic in the construction of the linearity test, the null hypothesis of $\gamma_\phi = \gamma_\theta = 0$ is tested by forming the appropriate LM-type test statistic based on a third order Taylor approximation of $H(t; *)$ around $\gamma_\phi = \gamma_\theta = 0$. This yields the auxiliary regression:

$$\begin{aligned}\Delta s_{t+1} = \delta_0' \mathbf{z}_t + \delta_1' \mathbf{z}_t \cdot G(s_t;\ \gamma, c) + \sum_{j=1}^{3} \delta_{j+1}'\, \tilde{\mathbf{z}}_t t^j \\ + \sum_{j=1}^{3} \delta_{j+4}' \tilde{\mathbf{z}}_t t^j \cdot G(s_t;\ \gamma, c) + u_t^*\end{aligned} \tag{6-18}$$

Under $H_0$ , $\delta_j = 0,\ j = 1,2,3,4,5,6,7.$ Following Eitrheim and Teräsvirta (1996), the null of parameter constancy is tested against three hypotheses:

- LM1: the parameters change monotonically over time;
- LM2: that the change is symmetric with respect to an unknown point in time;
- LM3: change is possibly non monotonic but not necessarily symmetric.

This is equivalent to testing the following null hypothesis:

$$H_3\text{:}\ \ \delta_2 = \delta_5 = 0\ given\ \delta_3 = \delta_4 = \delta_6 = \delta_7 = 0 \tag{6-19}$$

$$H_2\text{:}\ \ \delta_3 = \delta_6 = 0\ given\ \delta_4 = \delta_7 = 0 \tag{6-20}$$

$$H_1\text{:}\ \ \delta_4 = \delta_7 = 0 \tag{6-21}$$

We conclude that $\phi(t)$ and $\theta(t)$ in equation (6-15) are time variant and consistent with no structural change if either one of the above null hypotheses is rejected.

## 6.5 Empirical results

The empirical analysis in this chapter is based on the quarterly data of the exchange rate returns measured in log-differences and other economic fundamentals for the United Stated, the United Kingdom, Sweden and Australia, as used in the previous chapters. The time period for these countries is again different depending on the different measures of the wealth effect used. When the stock price represents the wealth effect, the data ranges from the first quarter of 1975 to the last quarter of 2008, whereas when house prices are used, the estimates use data from the first quarter of 1980.

Application of the linearity tests and the STAR models requires a stationary time series. Chapter 4 reported various unit root tests and the results indicated both exchange rates and fundamentals are stationary at the 5% significance level.

### 6.5.1 The linearity test results

Having confirmed stationarity for all variables, we can test for linearity. A summary of the results of the linearity tests can be found in Table 6-1 to Table 6-3. These tables provide the $p$-values of the LM tests, each country's Taylor rule exchange rate is tested against five potential transition variables belonging to the set of explanatory variables and exchange rate volatility. The first columns report the result of the test for linearity against non-linearity with the STR model (i.e. $H_0$ ). It can be seen that linearity is rejected against the STR model in twelve out of eighteen cases at the 10% significance level. For some cases, the $p$-value indicates extremely strong rejection. This confirms our theory regarding the nonlinear nature of the Taylor rule exchange rate model.[72] The following columns show results of the model selection test for choosing between LSTR and ESTR (i.e. $H_{01}$, $H_{02}$, $H_{03}$ ) and the chosen non-linear model specification. According to Teräsvirta (1994), since the three hypotheses ( $H_{01}$, $H_{02}$, $H_{03}$) can be simultaneously rejected, we choose the one with the strongest rejection.

It is interesting to note that not only do the results of linearization according to the different transition variables vary across country, but the transition variable giving the strongest evidence against linearity is also different for each country. In the case of the Swedish and UK exchange rate, exchange rate volatility gives the strongest rejection of the linearity test. However, this is not the case for Australia. In fact, the linearity test is insignificant when exchange rate volatility is taken as the transition variable. For Australia, the strongest rejection occurs when the real exchange rate is used as the transition variable.

The choice between LSTR and ESTR with regard to a particular transition variable is in general consistent across countries apart from when the output gap or volatility is the transition variable. When the lagged interest rate differential is the transition variable, the linearity test has been rejected for all the countries we studied and the model selection test consistently suggests the LSTR model is the best specification. The model selection is mixed when the output gap or exchange rate volatility are considered as the transition variable.

[72] Our prediction of nonlinear is coming from evidence of nonlinearity on both exchange rate models and Taylor rule interest rate from previous literature. The detail is discussed in section 6.2 literature review.

### Table 6-1 linearity tests- UK

| *Transition variable* | $H_0$ | $H_{01}$ | $H_{02}$ | $H_{03}$ | *Type of model* |
|---|---|---|---|---|---|
| $\pi_t - \tilde{\pi}_t$ | 0.2102 | 0.7110 | 0.7228 | 0.0172 | Linear |
| $y_t - \tilde{y}_t$ | 0.0118* | 0.1847 | 0.0310* | 0.0425 | ESTR |
| $i_{t-1} - \tilde{i}_{t-1}$ | 0.0283* | 0.2822 | 0.0853 | 0.0336* | LSTR |
| $w_t(s) - \tilde{w}_t(s)$ | 0.0601** | 0.2656 | 0.0351* | 0.2463 | ESTR |
| $\tilde{q}_t$ | 0.0755** | 0.0473* | 0.5596 | 0.0965 | LSTR |
| *volatility* | 0.0062* | 0.0695 | 0.0008 | 0.8983 | ESTR |

*Note:* the table show $p$-values of Teräsvirta (1994) linearity test, for which the null hypothesis of linearity is test against the alternative of STR model; the* and ** implies rejection of the null hypothesis at 5% and 10% significant level, respectively. If the $p$-value of the linearity test $H_0$ is less than significant level, the null is rejected, then we proceed to choose the one for which the $p$-value of the test is minimized among $H_{01}$, $H_{02}$ and $H_{03}$ and determine for which the best nonlinear model specification is going to be implemented.

### Table 6-2 linearity tests- Sweden

| *Transition variable* | $H_0$ | $H_{01}$ | $H_{02}$ | $H_{03}$ | *Type of model* |
|---|---|---|---|---|---|
| $\pi_t - \tilde{\pi}_t$ | 0.0090* | 0.0142* | 0.1912 | 0.0526 | LSTR |
| $y_t - \tilde{y}_t$ | 0.2050 | 0.0753 | 0.7366 | 0.2502 | Linear |
| $i_{t-1} - \tilde{i}_{t-1}$ | 0.0380* | 0.0105* | 0.2584 | 0.3091 | LSTR |
| $w_t(h) - \tilde{w}_t(h)$ | 0.0134* | 0.0735 | 0.0046* | 0.4984 | ESTR |
| $\Delta\tilde{q}_t$ | 0.3666 | 0.5038 | 0.0889 | 0.7752 | Linear |
| *volatility* | 0.0006* | 0.0030 | 0.0009* | 0.8954 | LSTR |

*Note:* see notes on Table 6-1.

### Table 6-3 linearity tests- Australian

| *Transition variable* | $H_0$ | $H_{01}$ | $H_{02}$ | $H_{03}$ | *Type of model* |
|---|---|---|---|---|---|
| $\pi_t - \tilde{\pi}_t$ | 0.2967 | 0.6039 | 0.1481 | 0.0518 | Linear |
| $y_t - \tilde{y}_t$ | 0.0040* | 0.0154* | 0.0867 | 0.0359 | LSTR |
| $i_{t-1} - \tilde{i}_{t-1}$ | 0.0032* | 0.0029* | 0.1698 | 0.0547 | LSTR |
| $w_t(s) - \tilde{w}_t(s)$ | 0.6889 | 0.5514 | 0.5853 | 0.5904 | Linear |
| $\tilde{q}_t$ | 0.0002* | 0.0188 | 0.4393 | 0.0000* | LSTR |
| *volatility* | 0.3034 | 0.0797 | 0.9328 | 0.2712 | Linear |

*Note:* see notes on Table 6-1.

Regarding the model selection, Teräsvirta (1994) suggests selecting the model with the smallest $p$-value in the linearity test. However, this procedure has drawbacks. Camacho (2004, pp.11) stated that: "one may find appropriate estimates and forecasts of the nonlinear model even if linearity is weakly rejected. Moreover, it is not clear what to do in case of similar p-values". As mentioned in the STR literature, the final decision on this can be postponed to the evaluation stage of the modelling strategy as in Teräsvirta (1994, 1996) and Dijk et al. (2002). In this study, we will follow the recommendation of Teräsvirta (1994). Observing every model passes the nonlinearity test as a potential candidate, estimating and check their adequacy when describing our data. The decision regarding the best performing model will be made based on the model evaluation and forecasting performance. Results from alternative STR models are described in the following subsections.

### 6.5.2 Nonlinear Estimation results

Table 6-4 to Table 6-14 shows the NLLS estimation results of the Taylor rule exchange rate model for each country considered.[73] Various specifications of the STR model are used with respect to different transition variables. Note that in estimating the speed parameter $\gamma$, Dijk et al. (2002) have argued that the result is often imprecise and that high levels of accuracy are not necessary. This is because large changes in $\gamma$ often only have a minor effect on the transition function. Moreover, estimates of $\gamma$ may appear to be insignificant. However, this does not imply weak non-linearity. Therefore, in analysing the results, we do not report its significance and only use it for comparing the relative speed of transition with other models.

Each estimated STR model is reported with a number of information criteria in order to access and compare the relative performance of the nonlinear and linear regression models. For example, we prefer the regression model which has higher values of $R^2$,

[73] The corresponding linear estimation results in Appendix III.

adjusted $R^2$ and log likelihood, but lower values of regression standard errors $\hat{\sigma}$. Moreover, we compute the sum of squared residuals ratio (i.e.$SSR_{ratio}$) between the STR model and the linear specification. A lower ratio (i.e. less than one) indicates a better fit for the nonlinear model and vice versa. Based on the above criteria, we found the STR model outperforms the linear model for all specifications of the STR models and in all the countries studied. Therefore, the linear relationship of the Taylor rule exchange rate can be improved by consideration of regime changes.

Across countries, the estimated threshold levels are strongly significantly different to zero for all chosen transition variables. Regarding the speed of transition $\gamma$, our results in general show a relatively moderate value except when exchange rate volatility is used as transition variable. This is proof of smooth transition between regimes. The transition from one regime to another for one particular transition variable varies across countries as reflected by the slope coefficient estimates $\gamma/\sigma_s\ (or\ \sigma_s^2)$. Among the different transition variables, exchange rate volatility offers the highest relative speed between regimes and at a low threshold level. This confirm the literature on nonlinear UIRP as lower volatility implies higher excess returns (i.e. High Sharpe ratio). This will attract speculative capital and force exchange rate quickly returns to the UIRP condition.

***Results for nonlinear UK/US exchange rate models***

The results of the various specifications of the STR models for the UK are presented in Table 6-4 and Table 6-5. In the case of the output gap, stock price difference or real exchange rate volatility being the transition variable, an ESTR model with a U-shaped transition function is the most appropriate. When the interest rate difference or the real exchange rate is used as the transition variable, the LSTR model is more appropriate.

The summary statistics suggest an ESTR specification with exchange rate volatility as the transition variable is the best model to capture nonlinearity in the exchange rate. This agrees with our results from the linearity test where exchange rate volatility provided a strong rejection of the null hypothesis. However, from the perspective of parameter estimation, the joint test gives a $p$-value of 0.764, suggesting the nonlinear part is jointly insignificant. This make sense as the high $\gamma$ make exchange rate transit from one regime to the other very quick and approximate to two linear relations. In case volatility is the transition function, changes in the exchange rate are mainly explained by the interest rate difference and real exchange rate. The situation is quite different when the interest rate difference or output gap is the transition variable. In these two models, the two macroeconomic indicators, the output gap and real exchange rate, become the main factors affecting exchange rates in a nonlinear way.

Another interesting result is that some of the estimated parameters have changed when switching to a nonlinear model, but as with the linear model, inflation enters insignificantly in both the linear and nonlinear part of the models. Inflation seems to play no role in the UK's exchange rate behaviour. This is a similar finding to Alcidi et al. (2007)'s result which shown insignificant of inflation in non-linear Taylor rule of UK over most of the estimation time span.

The results in Table 6-4 also show a significant threshold level for different transition variables. The ESTR specification with exchange rate volatility as the transition variable presents the largest smoothing parameter (i.e. $\gamma/\sigma_s$ =980462.30) which indicates a relatively sharp transition between two extreme regimes once exchange rate volatility is beyond the threshold level of 0.3%. The large smoothing parameter in our results contradicts the finding in Baillie and Chang (2011). However, their results are based on a study of the UIRP anomaly. The second highest is produced when the output gap is the transition variable. The others show much lower smoothing parameters. In all models, we note that the coefficients on the interest rate differences are very small in both the linear and nonlinear parts. Moreover, it enters the nonlinear part insignificantly in most of the specifications. This result indicates a low influence for the interest rate smoothing on the UK exchange rate (i.e. UK central bank interventions have limited influence on exchange rate movements).

**Table 6-4 Results from the nonlinear model - UK**

| | *(1)* | *(2)* | *(3)* | *(4)* | *(5)* |
|---|---|---|---|---|---|
| ***Sample*** | ***75Q1:08Q4*** | ***75Q1:08Q4*** | ***75Q1:08Q4*** | ***75Q1:08Q4*** | ***75Q1:08Q4*** |
| ***Model*** | ***ESTR*** | ***LSTR*** | ***ESTR*** | ***LSTR*** | ***ESTR*** |
| ***Transition variable ($s_t$)*** | $y_t - \tilde{y}_t$ | $i_{t-1} - \tilde{\imath}_{t-1}$ | $w_t - \tilde{w}_t(s)$ | $\tilde{q}_t$ | ***volatility*** |
| ***Linear part*** | | | | | |
| $\boldsymbol{\alpha_0}$ | 0.161* | 0.003 | 0.075** | -0.012 | 0.0455 |
| | (0.053) | (0.029) | (0.046) | (0.034) | (0.035) |
| $\boldsymbol{\beta_\pi}$ | 0.785 | -0.077 | -0.199 | 0.013 | -0.304 |
| | (0.601) | (0.207) | (0.414) | (0.196) | (0.314) |
| $\boldsymbol{\beta_y}$ | 2.821* | 0.138 | 1.216** | -0.173 | -0.238 |
| | (1.352) | (0.436) | (0.640) | (0.409) | (0.547) |
| $\boldsymbol{\beta_i}$ | 0.001 | 0.003 | 0.012* | 0.006* | 0.010* |
| | (0.003) | (0.003) | (0.004) | (0.002) | (0.003) |
| $\boldsymbol{\beta_w}$ | 0.226* | 0.173* | 0.273 | 0.091 | 0.018 |
| | (0.126) | (0.071) | (0.374) | (0.071) | (0.098) |
| $\boldsymbol{\beta_q}$ | -0.250* | -0.018 | -0.168* | -0.021 | -0.139* |
| | (0.080) | (0.052) | (0.079) | (0.067) | (0.069) |
| ***Nonlinear part*** | | | | | ***0.764*** |
| $\boldsymbol{\alpha_0^*}$ | -0.175* | 0.197* | 0.081 | 0.114 | 0.038 |
| | (0.068) | (0.069) | (0.073) | (0.144) | (0.090) |
| $\boldsymbol{\beta_\pi^*}$ | -0.909 | 0.173 | -0.052 | 0.211 | 1.139 |
| | (0.680) | (0.703) | (0.608) | (0.595) | (1.444) |
| $\boldsymbol{\beta_y^*}$ | -2.667** | 2.122* | -1.218 | 1.930* | 2.640 |
| | (1.445) | (0.931) | (0.921) | (0.892) | (1.783) |
| $\boldsymbol{\beta_i^*}$ | 0.003 | 0.001 | -0.016* | -0.006 | -0.021 |
| | (0.005) | (0.008) | (0.005) | (0.004) | (0.013) |
| $\boldsymbol{\beta_w^*}$ | -0.169 | -0.209 | 0.033 | 0.253 | 0.445 |
| | (0.178) | (0.218) | (0.262) | (0.252) | (0.336) |
| $\boldsymbol{\beta_q^*}$ | 0.257* | -0.362* | -0.130 | -0.213 | 0.058 |
| | (0.114) | (0.121) | (0.127) | (0.210) | (0.160) |
| ***Model parameters*** | | | | | |
| $\boldsymbol{\gamma}$ | 1.091 | 9.871 | 2.596 | 16.253 | 0.455 |
| $\boldsymbol{\gamma/\sigma_s}$ $(\boldsymbol{or\ \sigma_s^2})$ | 4164.052 | 3.856 | 516.118 | 117.63 | 980462.30 |
| $\boldsymbol{c}$ | -0.013* | 2.350* | -0.016* | 0.620* | 0.003* |
| | (0.003) | (0.387) | (0.007) | (0.000) | (0.000) |

*Note:* Table show coefficient of the variable over the entire sample period. Models are estimated by NLLS. The estimated standard errors are given in parentheses. $\gamma$ is the speed of transition between regimes. $\gamma/\sigma_s$ is the scaled speed for comparison across models. $c$ is the threshold value for particular transition variable.* and ** denote significant at the 5% and 10% level, respectively.

**Table 6-5 Results from the nonlinear model - UK (continue)**

| | *(1)* | *(2)* | *(3)* | *(4)* | *(5)* |
|---|---|---|---|---|---|
| ***Sample*** | ***75Q1:08Q4*** | ***75Q1:08Q4*** | ***75Q1:08Q4*** | ***75Q1:08Q4*** | ***75Q1:08Q4*** |
| ***Model*** | ***ESTR*** | ***LSTR*** | ***ESTR*** | ***LSTR*** | ***ESTR*** |
| ***Transition variable ($s_t$)*** | $y_t - \tilde{y}_t$ | $i_{t-1} - \tilde{\imath}_{t-1}$ | $w_t - \tilde{w}_t(s)$ | $\tilde{q}_t$ | ***volatility*** |
| ***Summary statistics*** | | | | | |
| $R^2$ | 0.223 | 0.235 | 0.234 | 0.246 | 0.295 |
| $adj.R^2$ | 0.137 | 0.151 | 0.154 | 0.163 | 0.218 |
| $SSR_{ratio}$ | 0.891 | 0.877 | 0.878 | 0.864 | 0.807 |
| $\hat{\sigma}$ | 0.048 | 0.047 | 0.047 | 0.046 | 0.045 |
| ***Log likelihood*** | 222.072 | 223.141 | 223.066 | 224.050 | 228.535 |

*Note:* $adj.R^2$ is the adjusted $R^2$ .$SSR_{ratio}$ denote sum of squared residuals ratio between the STR model and the linear specification. A lower ratio (i.e. less than one) indicates a better fit for the nonlinear model and vice versa. $\hat{\sigma}$ is the standard errors of regression. We prefer the regression model possessing higher values of $adj.R^2$, and log likelihood, but lower values of $SSR_{ratio}$ and $\hat{\sigma}$.

In order to investigate the adequacy of these different nonlinear specifications, we have performed several misspecification tests. Table 6-6 show the $p$-values of the JB test for normality, and ARCH-LM test for residual heteroscedasticity, the LM-autocorrelation test for lags 1 and 4, the parameter consistency test and the non-remaining linearity test. Overall, we found no empirical support for rejecting the null of residual heteroscedasticity, parameter constancy and no remaining nonlinearity for any of the chosen transition variables. However, there may be fourth order autocorrelation.[74]

[74] This is reflected by the result in Table 7-5 LM (4). I observed that in all cases, the failure to reject the null of no error autocorrelation at 10% significance level.

**Table 6-6 P-values of diagnostic tests for STR models - UK**

| | *(1)* | *(2)* | *(3)* | *(4)* | *(5)* |
|---|---|---|---|---|---|
| ***Sample*** | ***75Q1:08Q4*** | ***75Q1:08Q4*** | ***75Q1:08Q4*** | ***75Q1:08Q4*** | ***75Q1:08Q4*** |
| ***Model*** | ***ESTR*** | ***LSTR*** | ***ESTR*** | ***LSTR*** | ***ESTR*** |
| ***Transition variable*** ($s_t$) | $y_t - \tilde{y}_t$ | $i_{t-1} - \tilde{i}_{t-1}$ | $w_t - \tilde{w}_t(s)$ | $\tilde{q}_t$ | ***volatility*** |
| ***Residual Tests*** | | | | | |
| ***JB*** | 0.858 | 0.023* | 0.142 | 0.438 | 0.249 |
| ***ARCH-LM(1)*** | 0.945 | 0.629 | 0.461 | 0.985 | 0.799 |
| ***LM(1)*** | 0.812 | 0.587 | 0.066** | 0.441 | 0.283 |
| ***LM(4)*** | 0.007* | 0.103** | 0.013* | 0.049* | 0.018* |
| ***Remaining Nonlinearity*** | | | | | |
| $\pi_t - \tilde{\pi}_t$ | 0.814 | 0.592 | 0.868 | 0.736 | 0.868 |
| $y_t - \tilde{y}_t$ | 0.982 | 0.789 | 0.644 | 0.654 | 0.644 |
| $i_{t-1} - \tilde{i}_{t-1}$ | 0.858 | 0.928 | 0.793 | 0.367 | 0.793 |
| $w_t - \tilde{w}_t(s)$ | 0.436 | 0.225 | 0.519 | 0.229 | 0.519 |
| $\tilde{q}_t$ | 0.465 | 0.526 | 0.680 | 0.975 | 0.679 |
| ***volatility*** | 0.391 | 0.409 | 0.201 | 0.479 | 0.201 |
| ***Parameter Constancy*** | | | | | |
| $H_1$ | 0.847 | 0.670 | 0.699 | 0.966 | 0.698 |
| $H_2$ | 0.459 | 0.982 | 0.593 | 0.590 | 0.208 |
| $H_3$ | 0.994 | 0.995 | 0.969 | 0.973 | 0.861 |

*Note:* numbers in this table are $p$-values. * and ** represent rejection of the null at the 5% and 10% significance levels, respectively. JB denotes the Jarque-Bera test for the null of normality of residuals. LM (1) and LM (4) denote LM tests for the null of no first and forth order serial correlation. ARCH-LM (1) denotes the null of no first order residual heteroskedasticity. For parameter constancy, rejection of either one of the null $H_1$, $H_2$ and $H_3$ will lead a conclusion favouring parameter non-constancy, otherwise the parameters are time-invariant.

**Table 6-7 estimation after adjust for residual non-normality - UK**

| | | | | | |
|---|---|---|---|---|---|
| | *(2)* | | | *(2)* | |
| *Sample* | *75Q1:08Q4* | | | *75Q1:08Q4* | |
| *Model* | *LSTR* | | | *LSTR* | |
| *Transition variable ($s_t$)* | $i_{t-1} - \tilde{i}_{t-1}$ | | | $i_{t-1} - \tilde{i}_{t-1}$ | |
| *Linear part* | | *Nonlinear part* | | *Residual Tests* | |
| $\alpha_0$ | 0.003 (0.029) | $\alpha_0^*$ | 0.199* (0.067) | *JB* | 0.238 |
| $\beta_\pi$ | -0.078 (0.205) | $\beta_\pi^*$ | 0.144 (0.692) | *ARCH-LM(1)* | 0.802 |
| $\beta_y$ | 0.147 (0.432) | $\beta_y^*$ | 2.263* (0.913) | *LM(1)* | 0.563 |
| $\beta_i$ | 0.002 (0.003) | $\beta_i^*$ | 0.003 (0.008) | *LM(4)* | 0.147 |
| $\beta_w$ | 0.173* (0.070) | $\beta_w^*$ | -0.213 (0.215) | *Remaining Nonlinearity* | |
| $\beta_q$ | -0.017 (0.052) | $\beta_q^*$ | -0.385* (0.120) | $\pi_t - \tilde{\pi}_t$ | 0.564 |
| *Model parameters* | | | | $y_t - \tilde{y}_t$ | 0.810 |
| $\gamma$ | 10.547 | | | $i_{t-1} - \tilde{i}_{t-1}$ | 0.916 |
| $\gamma/\sigma_s\ (or\ \sigma_s^2)$ | 4.120 | | | $w_t - \tilde{w}_t(s)$ | 0.204 |
| $c$ | 2.322* (0.355) | | | $\tilde{q}_t$ | 0.556 |
| *Summary statistics* | | | | *volatility* | 0.474 |
| $R^2$ | 0.250 | | | *Parameter Constancy* | |
| $adj.R^2$ | 0.161 | | | $H_1$ | 0.568 |
| $SSR_{ratio}$ | 0.857 | | | $H_2$ | 0.894 |
| $\hat{\sigma}$ | 0.047 | | | $H_3$ | 0.992 |
| *Log likelihood* | 224.470 | | | | |

*Note:* this table present estimation and evaluation results after dummy variables introduced. Parameters are similar to the previous results, but all diagnostics tests results has improved.

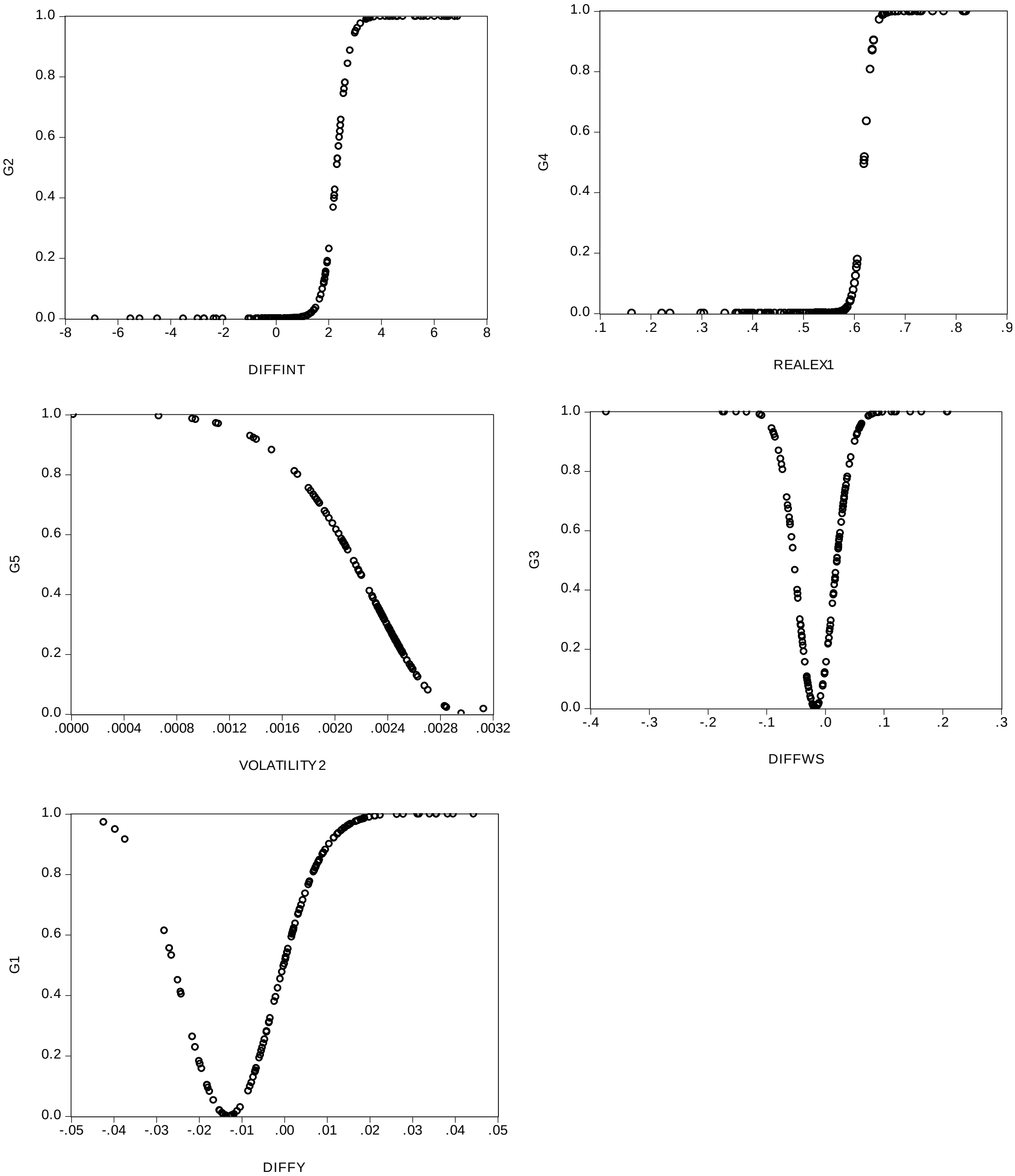
Moreover, with regard to the logistic STR models, there exists evidence of residual non-normality when the interest rate is the transition variable. We correct for non-normality by adding a dummy variable for 1988Q1.[75] The results are shown in Table 6-7. Comparing the two models, the parameter estimates are similar to the ones before but the one with the dummy variables is improved with no evidence of residual normality or autocorrelation.

Overall, based on the results of the misspecification tests, the Logistic STR models with the interest rate difference as the transition variable are well specified and prevail over other models. In particular, the model passed all residual tests, the parameters seems to be constant over time and there is little evidence of any remaining nonlinearity of the STR-type.

Additionally, we have plotted the estimated transition function over time and against different transition variables. Figure 6-3 shows the shape of the transition function. Each point indicates a single observation of the transition variable, so that one can readily see which values the transition function has obtained and how frequently. In all cases studied, there are a reasonable number of observations for both sides of $c$, which provides confidence in our selection of ESTR and LSTR. Moreover, there are an even distribution of observations between the two extreme regimes which provides evidence of smooth transition between regimes.

[75] This represents the time that the UK government tried to stabilize the exchange rate by largely intervening in the foreign exchange market and changing interest rates.

**Figure 6-3 Estimated transition function as a function of transition variable – UK**



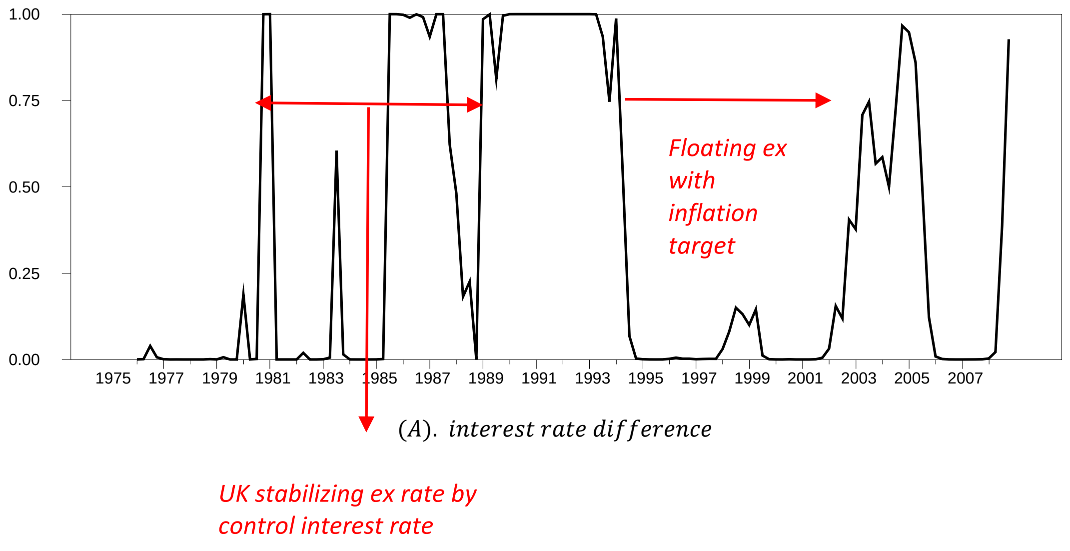

*Note:* figures display the plots of the estimated transition functions, $G(.)$, against different transition variables.

Figure 6-4 shows plots of the same information over time during our sample period, which helps in understanding the nonlinear behaviour of different transition variables. In the cases where the interest rate difference or real exchange rate are the transition variable, the transition starting points are almost identical with the first transition at the beginning of 1979. This is the time that the authorities' objective of nominal exchange rate stability begins to conflict with their monetary targeting, with the monetary target at risk of being overshot and unsustainable and at the same time Sterling appreciated to a great extent as UK interest rates increased sharply. The fluctuation of the interest rate between regimes approximately between 1979 and 1988 together with a stable exchange rate corresponds to the period that the UK tried to stabilize the exchange rate by controlling interest rates. From these figures, it is interesting to note that the transition functions between 1989 and 1994 are very close to unity and after 1994, they attained zero more often. This is the same as the results of Baillie and Kiliç (2006). Baillie and Kiliç (2006) argued this can been explained by the fact that the US has lower interest rates than the UK, and US dollars were quoted at a premium during this period approximately between 1989 and 1994. Figures (c) and (d) show the output gap and the stock price transition. Compared with the others, the two figures represent a rapid shift between regimes. This is another indication of the nonlinear character of the models, revealing the fact that there is a frequent shift of the output gap and stock price relative to the exchange rate change over the period studied. The rapid transition also confirms the high speed of the parameters in the estimation. Another interesting finding is that in general larger changes in parameters occurred more frequently prior to 1992. After this date, the UK has adopted inflation targeting with no great changes in monetary policy. This coincides in our figure with the parameters of our nonlinear Taylor rule type exchange rate relationship generally changing less often after 1992.[76] This also coincides with the UK leaving the ERM in September of 1992, so subsequently being

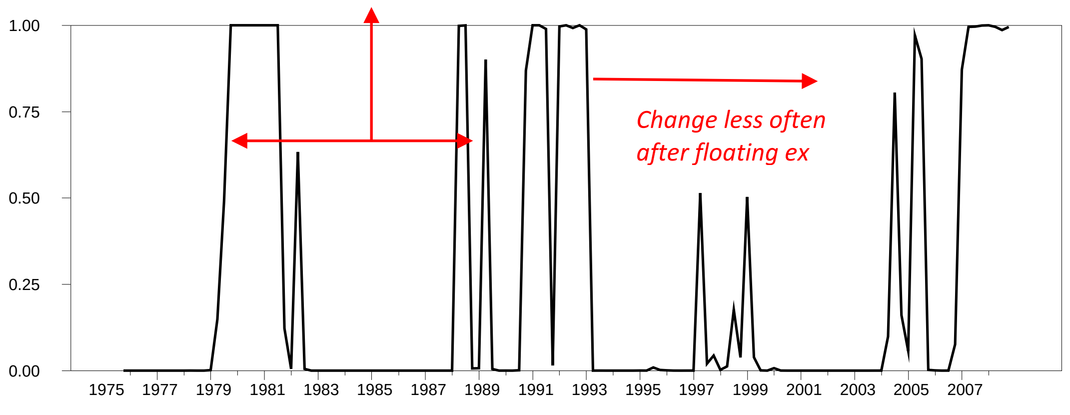
[76] The fact there are lower parameter changes in the nonlinear Taylor rule after 1992 has already been proven by Brüggemann and Riedel (2011).

able to use monetary policy to stabilise the domestic economy, rather than keep its exchange rate within the ERM bands.

**Figure 6-4 Estimated transition function over time**



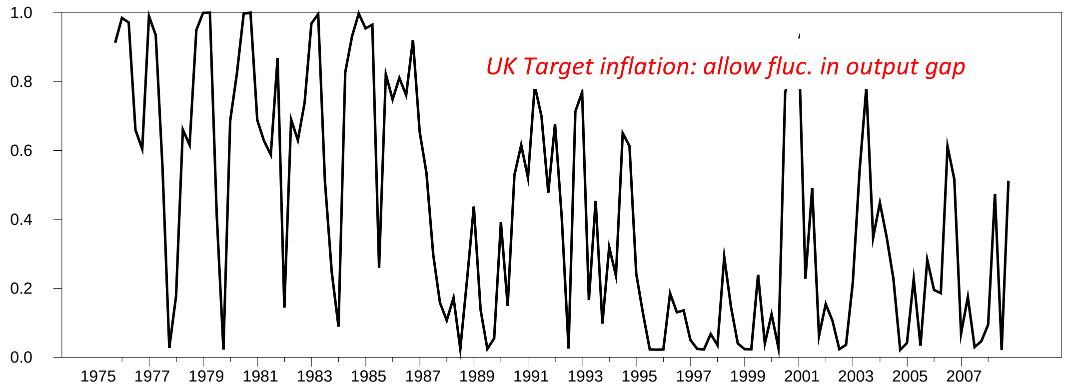

$(A).\ interest\ rate\ difference$



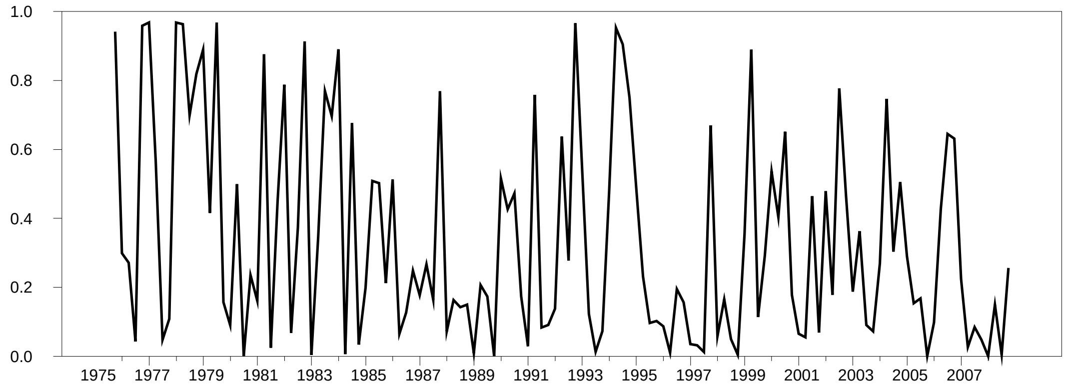

$(B).\ real\ exchange\ rate$

*Note:* figures display the plots of the estimated transition functions, $G(.)$, over time. (A) and (B) are the logistic transition functions with interest rate difference and real exchange rate as the transition variables, respectively.

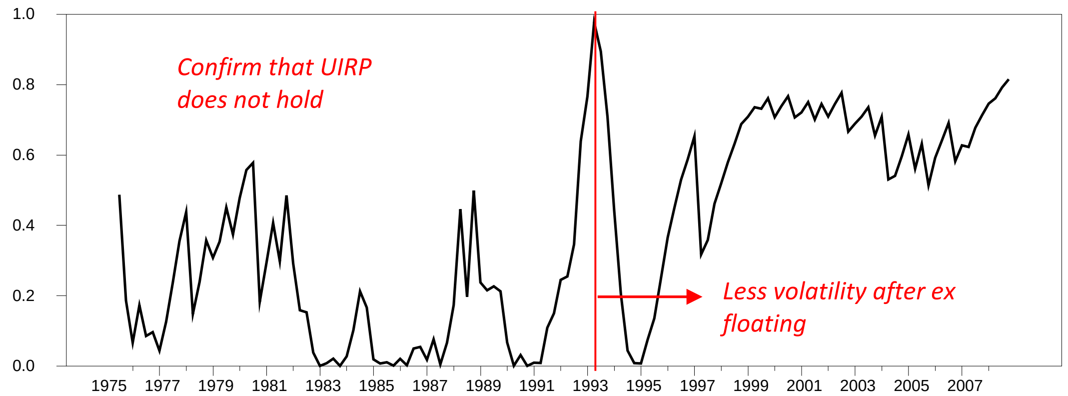
**Figure 6-5 Estimated transition function over time (continue)**




$(C).\ output\ difference$



$(D).stock\ price\ difference$




$(E).exchange\ rate\ volatility$

*Note:* figures display the plots of the estimated transition functions, $G(.)$, over time. (C), (D) and (E) are the exponential transition functions with output gap difference, stock price difference and exchange rate volatility as the transition variables, respectively.

### *Results for nonlinear Sweden/US exchange rate models*

Table 6-8, Table 6-9 and Table 6-10 show least squares estimation results and the result of diagnostic statistics for Sweden with regard to different transition variables. In the original models, we found the Jarque-Bera normality test has been rejected for all specifications. Therefore, dummy variables have been introduced into these models to overcome the problem of normality in the error term.[77] The estimation and evaluation results from the original models are listed in Appendix IV.

Before analysing the model, it is worth checking whether the nonlinearities are due to the presence of these outliers. Using the same method applied by Sarantis (1999),[78] we compare the estimation results of these two models and observed similar patterns as in Sarantis (1999). The parameter estimation results are very close to each other apart from when exchange rate volatility is used as the transition variable. Therefore, we conclude that nonlinearities in Sweden's exchange rate are not due to the effect of any outliers. In the model specification where exchange rate volatility is the transition variable, we observe a smoother transition between regimes, as reflected by a largely reduced speed of transition. Significant parameters in the nonlinear part of the model such as inflation, the wealth effect and real exchange rate in the specification without dummies becomes no longer significant once dummies are added. However, the fact that adding dummy variables will reduce volatility in the exchange rate offers an explanation for the above difference. A visual inspection of

[77] The two dummy variables added to the models are 1993Q3 and 2008Q4. 2008Q4 represents the time of the financial crisis and 1993Q3 is around the time that the Governing Board of the Riksbank in Sweden announced to apply inflation targets and the Swedish economy had begun to recover.

[78] Sarantis (1999) checks for the nonlinearities due to the presence of outliers by using dummies to filter them out. He argued that if all estimated parameters and diagnostic statistics are similar as before with residuals becoming normal, then we can conclude that nonlinearity is not the outcome of outliers.

**Table 6-8 Estimation results from the nonlinear model – Sweden**

| | ***(1)*** | ***(2)*** | ***(3)*** | ***(4)*** |
|---|---|---|---|---|
| ***Sample*** | ***80Q1:08Q4*** | ***80Q1:08Q4*** | ***80Q1:08Q4*** | ***80Q1:08Q4*** |
| ***Model*** | ***LSTR*** | ***LSTR*** | ***ESTR*** | ***LSTR*** |
| ***Transition variable ($s_t$)*** | $\pi_t - \tilde{\pi}_t$ | $i_{t-1} - \tilde{i}_{t-1}$ | $w_t(h) - \tilde{w}_t(h)$ | ***volatility*** |
| ***Linear part*** | ***0.010*** | | | |
| $\alpha_0$ | -0.039 | -0.066* | 0.009 | 0.007 |
| | (0.134) | (0.023) | (0.007) | (0.007) |
| $\beta_\pi$ | -2.674 | -0.383 | 0.849* | 0.282 |
| | (3.482) | (0.589) | (0.352) | (0.273) |
| $\beta_y$ | -1.313 | 1.673* | -0.906** | -0.654** |
| | (0.904) | (0.666) | (0.521) | (0.395) |
| $\beta_i$ | 0.008 | 0.009* | -0.010* | -0.005* |
| | (0.008) | (0.002) | (0.003) | (0.002) |
| $\beta_w$ | 0.148 | -0.392 | -0.020 | 0.085 |
| | (0.236) | (0.251) | (0.273) | (0.184) |
| $\beta_q$ | -0.075 | -0.023 | -0.101 | 0.038 |
| | (0.167) | (0.127) | (0.124) | (0.089) |
| ***Nonlinear part*** | | | | |
| $\alpha_0^*$ | 0.283 | 0.074* | -0.124** | -0.185 |
| | (0.395) | (0.024) | (0.075) | (0.164) |
| $\beta_\pi^*$ | -0.320 | 0.980 | -9.842* | 0.246 |
| | (1.134) | (0.673) | (2.836) | (0.169) |
| $\beta_y^*$ | 2.498 | -2.713* | 3.193 | 3.908 |
| | (1.822) | (0.911) | (3.174) | (3.197) |
| $\beta_i^*$ | -0.029* | -0.015* | 0.084* | 0.023* |
| | (0.015) | (0.004) | (0.016) | (0.011) |
| $\beta_w^*$ | 0.049 | 0.620** | 1.081 | -0.723 |
| | (0.491) | (0.337) | (1.242) | (1.728) |
| $\beta_q^*$ | 0.346 | -0.004 | -0.290 | -1.060 |
| | (0.357) | (0.185) | (0.584) | (0.672) |
| ***Model parameters*** | | | | |
| $\gamma$ | 1.757 | 27.316 | 0.096 | 2.885 |
| $\gamma/\sigma_s\ (or\ \sigma_s^2)$ | 73.224 | 6.568 | 47.977 | 4331.120 |
| $c$ | 0.005* | 2.882* | 0.017* | 0.005* |
| | (0.000) | (0.000) | (0.000) | (0.000) |

*Note:* Table show coefficient of the variable over the entire sample period. Models are estimated by NLLS. The estimated standard errors are given in parentheses. $\gamma$ is the speed of transition between regimes. $\gamma/\sigma_s$ is the scaled speed for comparison across models. $c$ is the threshold value for particular transition variable.* and ** denote significant at the 5% and 10% level, respectively.

**Table 6-9 Estimation results from the nonlinear model – Sweden (continue)**

| | *(1)* | *(2)* | *(3)* | *(4)* |
|---|---|---|---|---|
| ***Sample*** | ***80Q1:08Q4*** | ***80Q1:08Q4*** | ***80Q1:08Q4*** | ***80Q1:08Q4*** |
| ***Model*** | ***LSTR*** | ***LSTR*** | ***ESTR*** | ***LSTR*** |
| ***Transition variable ($s_t$)*** | $\boldsymbol{\pi_t - \tilde{\pi}_t}$ | $\boldsymbol{i_{t-1} - \tilde{i}_{t-1}}$ | $\boldsymbol{w_t(h) - \tilde{w}_t(h)}$ | ***volatility*** |
| ***Summary statistics*** | | | | |
| $\boldsymbol{R^2}$ | 0.412 | 0.451 | 0.463 | 0.463 |
| $\boldsymbol{adj.R^2}$ | 0.321 | 0.353 | 0.367 | 0.367 |
| $\boldsymbol{SSR_{ratio}}$ | 0.6391 | 0.5956 | 0.5820 | 0.5820 |
| $\boldsymbol{\hat{\sigma}}$ | 0.049 | 0.048 | 0.047 | 0.047 |
| ***Log likelihood*** | 188.678 | 192.615 | 193.847 | 193.838 |

*Note:* $adj.R^2$ is the adjusted $R^2$ .$SSR_{ratio}$ denote sum of squared residuals ratio between the STR model and the linear specification. A lower ratio (i.e. less than one) indicates a better fit for the nonlinear model and vice versa. $\hat{\sigma}$ is the standard errors of regression. We prefer the regression model possessing higher values of $adj.R^2$, and log likelihood, but lower values of $SSR_{ratio}$ and $\hat{\sigma}$.

the reduced volatility from Figure IV-1 in the Appendix IV to Figure 6-7 also confirms this fact.

Focusing on column (1) of Table 6-8 with the inflation difference as the transition variable, we observe that none of the coefficients associated with the linear part are statistically significantly different from zero. This does not mean the model can be purely explained by the nonlinear part since the $F$-test suggests the linear part is jointly significant at the 1% level of significance.

Moreover, we note that the real exchange rate which plays no role in the linear regression is also insignificant in the nonlinear models. This evidence suggests the central bank of Sweden does not attempt to control the exchange rate by maintaining it within some bounds, Moreover, it explains why the nonlinearity test failed when the real exchange rate was used as a transition variable.

**Table 6-10 P-values of the diagnostic tests for STR models – Sweden**

| | *(1)* | *(2)* | *(3)* | *(4)* |
|---|---|---|---|---|
| ***Sample*** | ***80Q1:08Q4*** | ***80Q1:08Q4*** | ***80Q1:08Q4*** | ***80Q1:08Q4*** |
| ***Model*** | ***LSTR*** | ***LSTR*** | ***ESTR*** | ***LSTR*** |
| ***Transition variable ($s_t$)*** | $\boldsymbol{\pi_t - \tilde{\pi}_t}$ | $\boldsymbol{i_{t-1} - \tilde{i}_{t-1}}$ | $\boldsymbol{w_t - \tilde{w}_t(h)}$ | ***volatility*** |
| ***Residual Tests*** | | | | |
| ***JB*** | 0.143 | 0.102 | 0.187 | 0.273 |
| ***ARCH-LM(1)*** | 0.259 | 0.826 | 0.676 | 0.690 |
| ***LM(1)*** | 0.026* | 0.551 | 0.334 | 0.497 |
| ***LM(4)*** | 0.188 | 0.763 | 0.594 | 0.695 |
| ***Remaining Nonlinearity*** | | | | |
| $\boldsymbol{\pi_t - \tilde{\pi}_t}$ | 0.994 | 0.154 | 0.458 | 0.593 |
| $\boldsymbol{y_t - \tilde{y}_t}$ | 0.707 | 0.792 | 0.873 | 0.340 |
| $\boldsymbol{i_{t-1} - \tilde{i}_{t-1}}$ | 0.073** | 0.925 | 0.860 | 0.974 |
| $\boldsymbol{w_t(h) - \tilde{w}_t(h)}$ | 0.967 | 0.929 | 0.999 | 0.892 |
| $\Delta \boldsymbol{\tilde{q}_t}$ | 0.495 | 0.302 | 0.962 | 0.532 |
| ***volatility*** | 0.693 | 0.810 | 0.811 | 0.916 |
| ***Parameter Constancy*** | | | | |
| $\boldsymbol{H_1}$ | 0.475 | 0.169 | 0.848 | 0.018* |
| $\boldsymbol{H_2}$ | 0.501 | 0.452 | 0.905 | 0.777 |
| $\boldsymbol{H_3}$ | 0.999 | 0.965 | 0.997 | 0.999 |

*Note:* numbers in this table are $p$-values. * and ** represent rejection of the null at the 5% and 10% significance levels, respectively. JB denotes the Jarque-Bera test for the null of normality of residuals. LM (1) and LM (4) denote LM tests for the null of no first and forth order serial correlation. ARCH-LM (1) denotes the null of no first order residual heteroskedasticity. For parameter constancy, rejection of either one of the null $H_1$, $H_2$ and $H_3$ will lead a conclusion favouring parameter non-constancy, otherwise the parameters are time-invariant.

The result that the estimated transition parameter appears to be significantly different from zero indicates that the Taylor rule exchange rate regressions are indeed highly nonlinear. The highest speed of transition occurs when the exchange rate volatility exceeds a threshold level of 0.5%. Other models, such as the LSTR model with interest rate differences as the transition variable, show a much lower smoothing parameter.

A scatter plot of the transition variables against their estimated transition functions are shown in Figure 6-6. These figures display strongly nonlinear behavior and give supportive evidence of the smooth change between two extreme regimes in most of the cases. Note that when volatility is the transition variable, the estimated threshold is above the halfway point between regimes.[79] Therefore, almost all observations belong to the left hand tail of the transition function as is seen from the figure. The value of the transition function has remained close to zero for most of the volatility values. Thus a linear model would do almost the same job as the LSTR model. However, since the LSTR model had a better fit and there is indeed some evidence of nonlinearity shown by both the figure and the test, it is reported here. When inflation is the transition variable, the function moves between two extreme regimes with few lying on the two extreme regimes. In the case of the interest rate difference as the transition variable, the model is closer to a discrete regime switching model with a relatively large number of observations on the two extreme regimes and a relatively sharp transition. The same information can also been found in Figure 6-7 and Figure 6-8.

Over the period studied, different criteria are consistent in selecting models (3) and (4) as the best fitting model. In line with the results of the nonlinearity tests, model (4), the logarithm specification with volatility as the transition function is also the specification producing the lowest $p$-value in the linearity test. However, the estimation result from specification (3) supports the findings of Camacho (2004), as the specification fits as well as model (4) but has a higher $p$-value in the nonlinearity test. Moreover, results from the diagnostic and adequacy tests in Table 6-10 suggest model (3) is more robust than model (4). When the house price is the transition

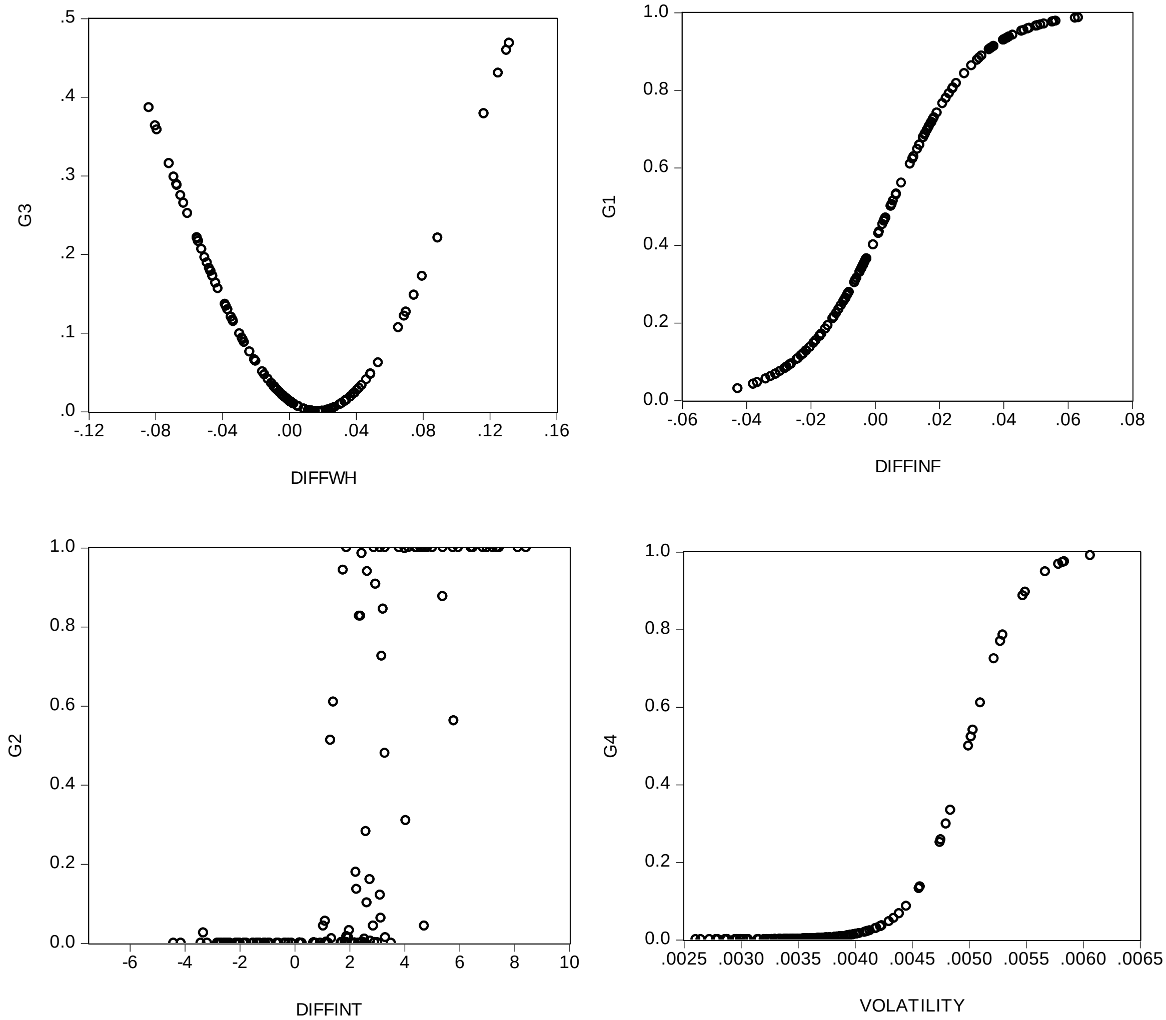
[79] The mean and medium points for volatility are 0.00383 and 0.00365 respectively.

variable, the equation passes all diagnostic tests. Whereas when exchange rate volatility is the transition, there is evidence of parameter inconsistency in the way that the parameter may change monotonically over time. The other model which passes all misspecification tests is the logarithm STR model with interest rates as the transition variable. When the inflation difference is used, some evidence of nonlinearity exists but it is not very strong.

Figure 6-7 and Figure 6-8 presents the movements of different estimated transition functions over time. These plots show different speeds of fluctuations over the sample period studied, which give a further indication of the nonlinear nature of the exchange rate changes. Moreover, the change of parameters which depending on different transition variables, can also be viewed as an indicator of the overall economic conditions or the monetary policy stance in Sweden. It is interesting to observe that despite the variation in the model and the use of different transition variables in these transition functions, the large change in parameters and the frequent shift of transition functions all end around 1994. After 1994, the transition functions stay in the lower regime most of the time and parameters changes less often. This pattern is in accordance with the Swedish economic policy, which experienced large interventions in the foreign exchange markets during the fixed rate regime period (i.e. before 1990) following the crisis and policy realignment of the Swedish economy in early 1990 and then finally a stabilised economy with no great changes in monetary policy after the end of 1995.[80] We note that approximately between the periods 1990 to 1994, the transition functions attained values mostly in the upper regime with values close to unity. This is consistent with the fact that Sweden had experienced a severe economic crisis in the early 90s, following their banking crisis and they experienced large changes in monetary policy.

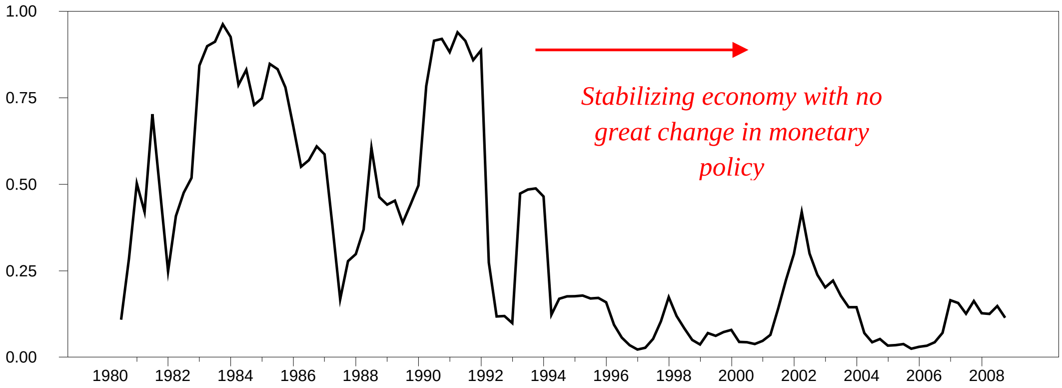
[80] Sweden monetary and exchange rate policy has been discussed in more detail in section 3.2.

**Figure 6-6 Estimated transition function as a function of transition variable – Sweden**

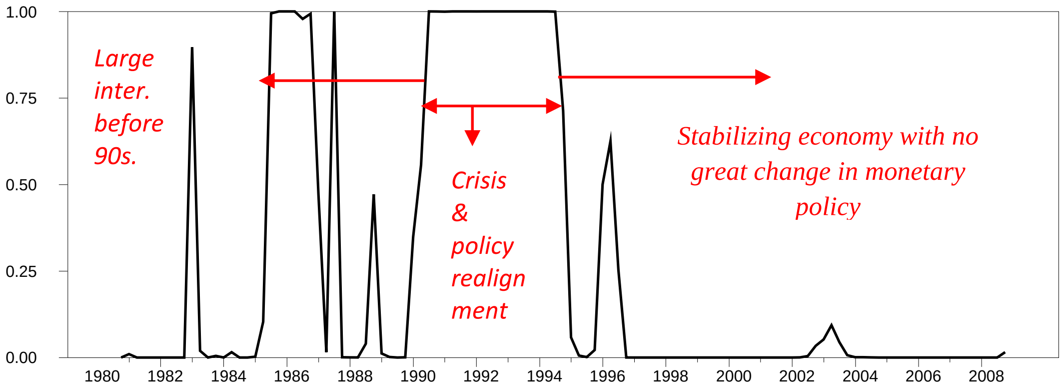



*Note:* figures display the plots of the estimated transition functions, $G(.)$, against different transition variables.

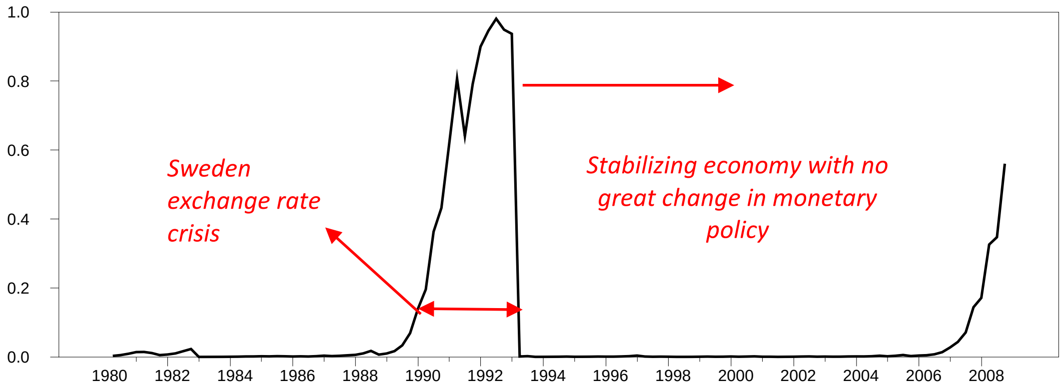
**Figure 6-7 Estimated transition function over time - Sweden**




$(A).\ inflation\ difference$



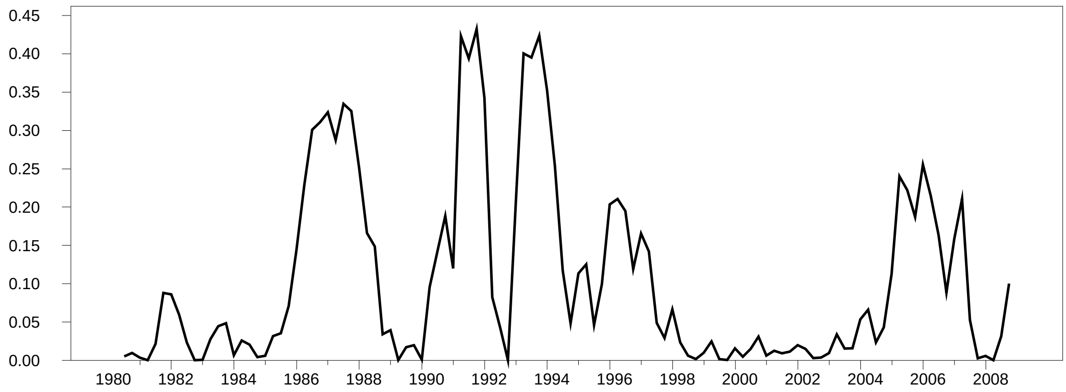

$(B).\ interest\ rate\ difference$




$(C).\ exchange\ rate\ volatility$

*Note:* figures display the plots of the estimated transition functions, $G(.)$, over time. (A), (B) and (C) are the logistic transition functions with inflation difference, interest rate difference and exchange rate volatility as the transition variables, respectively.

**Figure 6-8 Estimated transition function over time – Sweden (*continue*)**




*Note:* figures display the plots of the estimated exponential transition function, $G(.)$, over time with house price difference as the transition variable.

### *Results for nonlinear Australia/US exchange rate models*

The results in Table 6-3 for various specifications of the Australian exchange rate indicate the validity of the logarithmic STR model. Evidence of nonlinearity exists when the output gap, interest rate difference or real exchange rate are used as the transition variable, and all suggest a logistic transition function is best in describing the nonlinear behaviour of the exchange rate. The models are different from the models of Sweden and the UK in the sense that it not only fits better than the linear ones, but also produces the highest coefficient of determination among the countries studied.

As with the Swedish exchange rate, the nonlinear model of the Australian exchange rate contains outliers (i.e. the Jarque-Bera test for the initial estimates rejects the normality assumption). Therefore, dummy variables have been introduced into the model to resolve this problem.[81] Table 6-11, Table 6-12 and Table 6-13 list the results after the non-normality in the error term has been adjusted by including dummies in regression, whereas the results before this adjustment are listed in Tables IV-4, Table IV-5 and Table IV-6 of the Appendix IV.

[81] Dummy variables added in the model are 2008Q4, 1986Q3 and 1985Q2.

**Table 6-11 Estimation results from the nonlinear model – Australia**

| | *(1)* | *(2)* | *(3)* |
|---|---|---|---|
| ***Sample*** | ***75Q1:08Q4*** | ***75Q1:08Q4*** | ***75Q1:08Q4*** |
| ***Model*** | ***LSTR*** | ***LSTR*** | ***LSTR*** |
| ***Transition variable ($s_t$)*** | $y_t - \tilde{y}_t$ | $i_{t-1} - \tilde{i}_{t-1}$ | $\tilde{q}_t$ |
| ***Linear part*** | | | ***0.304*** |
| $\alpha_0$ | -0.013 | -0.016 | -0.639 |
| | (0.011) | (0.012) | (5.098) |
| $\beta_\pi$ | 0.147 | 0.274 | -0.773 |
| | (0.223) | (0.310) | (2.604) |
| $\beta_y$ | -0.252 | -0.673** | 1.195 |
| | (0.406) | (0.394) | (4.556) |
| $\beta_i$ | 0.002 | 0.004 | 0.014 |
| | (0.002) | (0.003) | (0.037) |
| $\beta_w$ | 0.102* | 0.155* | -0.113 |
| | (0.044) | (0.058) | (0.715) |
| $\beta_q$ | -0.024 | -0.006 | -0.732 |
| | (0.032) | (0.039) | (4.515) |
| ***Nonlinear part*** | ***0.818*** | | ***0.608*** |
| $\alpha_0^*$ | -0.021 | -0.040 | 0.878 |
| | (0.075) | (0.047) | (8.202) |
| $\beta_\pi^*$ | 0.363 | -0.408 | 2.007 |
| | (0.757) | (0.579) | (5.213) |
| $\beta_y^*$ | -1.355 | 1.511** | -3.185 |
| | (1.473) | (0.915) | (9.037) |
| $\beta_i^*$ | 0.001 | -0.011** | -0.027 |
| | (0.004) | (0.006) | (0.075) |
| $\beta_w^*$ | -0.079 | -0.172 | 0.464 |
| | (0.159) | (0.112) | (1.443) |
| $\beta_q^*$ | -0.184 | -0.360** | -0.526 |
| | (0.197) | (0.197) | (1.471) |
| ***Model parameters*** | | | |
| $\gamma$ | 6.856 | 4.163 | 0.618 |
| $\gamma/\sigma_s\ (or\ \sigma_s^2)$ | 358.973 | 1.312 | 3.910 |
| $c$ | 0.017** | 3.613* | -0.376* |
| | (0.009) | (0.946) | (0.000) |

*Note:* Table show coefficient of the variable over the entire sample period. Models are estimated by NLLS. The estimated standard errors are given in parentheses. $\gamma$ is the speed of transition between regimes. $\gamma/\sigma_s$ is the scaled speed for comparison across models. $c$ is the threshold value for particular transition variable.* and ** denote significant at the 5% and 10% level, respectively.

**Table 6-12 Estimation results from the nonlinear model – Australia (continue)**

| | *(1)* | *(2)* | *(3)* |
|---|---|---|---|
| ***Sample*** | ***75Q1:08Q4*** | ***75Q1:08Q4*** | ***75Q1:08Q4*** |
| ***Model*** | ***LSTR*** | ***LSTR*** | ***LSTR*** |
| ***Transition variable ($s_t$)*** | $y_t - \tilde{y}_t$ | $i_{t-1} - \tilde{i}_{t-1}$ | $\tilde{q}_t$ |
| ***Summary statistics*** | | | |
| $R^2$ | 0.564 | 0.610 | 0.564 |
| $adj.R^2$ | 0.490 | 0.544 | 0.503 |
| $SSR_{ratio}$ | 0.480 | 0.429 | 0.478 |
| $\hat{\sigma}$ | 0.043 | 0.041 | 0.043 |
| ***Log likelihood*** | 238.411 | 245.795 | 238.496 |

*Note:* $adj.R^2$ is the adjusted $R^2$ .$SSR_{ratio}$ denote sum of squared residuals ratio between the STR model and the linear specification. A lower ratio (i.e. less than one) indicates a better fit for the nonlinear model and vice versa. $\hat{\sigma}$ is the standard errors of regression. We prefer the regression model possessing higher values of $adj.R^2$, and log likelihood, but lower values of $SSR_{ratio}$ and $\hat{\sigma}$.

When comparing these two sets of results, we found that the parameter estimates and diagnostic statistics have changed substantially. Particularly in the STR model specifications (1) and (3), when the output gap or real exchange rate acts as the transition variables, the nonlinear part becomes jointly insignificantly different from zero after the dummy variables were added.

So, nonlinearity may no longer exist in the STR model for the output gap and real exchange rate. This is further confirmed by the results listed in Table 6-14 which is the linearity test after the dummy variables were added. We observe that apart from transition due to interest rate differences, the Australian exchange rate performs in a linear fashion. The misspecification test on the residuals shows the residuals have now become normal and the autocorrelation has also been resolved. So, nonlinear transition in the Australian exchange rate is due largely as a result of the outliers.

**Table 6-13 P-values of diagnostic tests for STR models - Australia**

| | *(1)* | *(2)* | *(3)* |
|---|---|---|---|
| ***Sample*** | ***75Q1:08Q4*** | ***75Q1:08Q4*** | ***75Q1:08Q4*** |
| ***Model*** | ***LSTR*** | ***LSTR*** | ***LSTR*** |
| ***Transition variable ($s_t$)*** | $y_t - \tilde{y}_t$ | $i_{t-1} - \tilde{i}_{t-1}$ | $\tilde{q}_t$ |
| ***Residual Tests*** | | | |
| ***JB*** | 0.395 | 0.153 | 0.346 |
| ***ARCH-LM(1)*** | 0.735 | 0.797 | 0.532 |
| ***LM(1)*** | 0.121 | 0.320 | 0.471 |
| ***LM(4)*** | 0.215 | 0.775 | 0.745 |
| ***Remaining Nonlinearity*** | | | |
| $\pi_t - \tilde{\pi}_t$ | 0.750 | 0.584 | 0.463 |
| $y_t - \tilde{y}_t$ | 0.939 | 0.653 | 0.771 |
| $i_{t-1} - \tilde{i}_{t-1}$ | 0.532 | 0.992 | 0.278 |
| $w_t(s) - \tilde{w}_t(s)$ | 0.849 | 0.881 | 0.915 |
| $\tilde{q}_t$ | 0.992 | 0.896 | 0.998 |
| ***volatility*** | 0.453 | 0.606 | 0.229 |
| ***Parameter Constancy*** | | | |
| $H_1$ | 0.790 | 0.986 | 0.377 |
| $H_2$ | 0.459 | 0.492 | 0.012* |
| $H_3$ | 0.998 | 0.999 | 0.788 |

*Note:* numbers in this table are $p$-values. * and ** represent rejection of the null at the 5% and 10% significance levels, respectively. JB denotes the Jarque-Bera test for the null of normality of residuals. LM (1) and LM (4) denote LM tests for the null of no first and forth order serial correlation. ARCH-LM (1) denotes the null of no first order residual heteroskedasticity. For parameter constancy, rejection of either one of the null $H_1$, $H_2$ and $H_3$ will lead a conclusion favouring parameter non-constancy, otherwise the parameters are time-invariant.

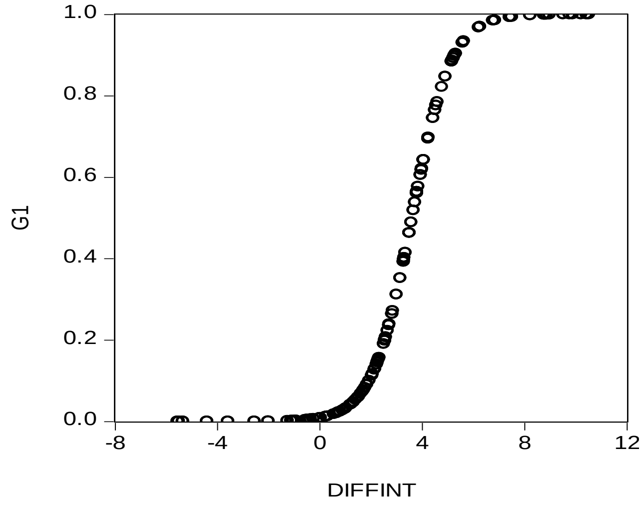
**Table 6-14 linearity test (after adjustment) - Australia**

| *Transition variable* | $H_0$ | $H_{01}$ | $H_{02}$ | $H_{03}$ | *Type of model* |
|---|---|---|---|---|---|
| $\boldsymbol{\pi_t - \tilde{\pi}_t}$ | 0.1671 | 0.5251 | 0.9532 | 0.0051 | Linear |
| $\boldsymbol{y_t - \tilde{y}_t}$ | 0.6697 | 0.7711 | 0.3310 | 0.7468 | Linear |
| $\boldsymbol{i_{t-1} - \tilde{i}_{t-1}}$ | 0.0178* | 0.0046* | 0.8667 | 0.0086 | LSTR |
| $\boldsymbol{w_t(s) - \tilde{w}_t(s)}$ | 0.1554 | 0.0710 | 0.3478 | 0.1298 | Linear |
| $\boldsymbol{\tilde{q}_t}$ | 0.1654 | 0.6119 | 0.1710 | 0.0755 | Linear |
| ***volatility*** | 0.1561* | 0.0058 | 0.7650 | 0.6237 | Linear |

*Note*: the table show p-values of linearity test after introduce dummy variables in models for which the null hypothesis of linearity is test against the alternative of STR model; the* and ** implies rejection of the null hypothesis at 5% and 10% significant level, respectively. If the $\boldsymbol{p}$-value of the linearity test $\boldsymbol{H_0}$ is less than significant level, the null is rejected, then we proceed to choose the one for which the $\boldsymbol{p}$-value of the test is minimized among $\boldsymbol{H_{01}}$, $\boldsymbol{H_{02}}$ and $\boldsymbol{H_{03}}$ and determine for which the best nonlinear model specification is going to be implemented.

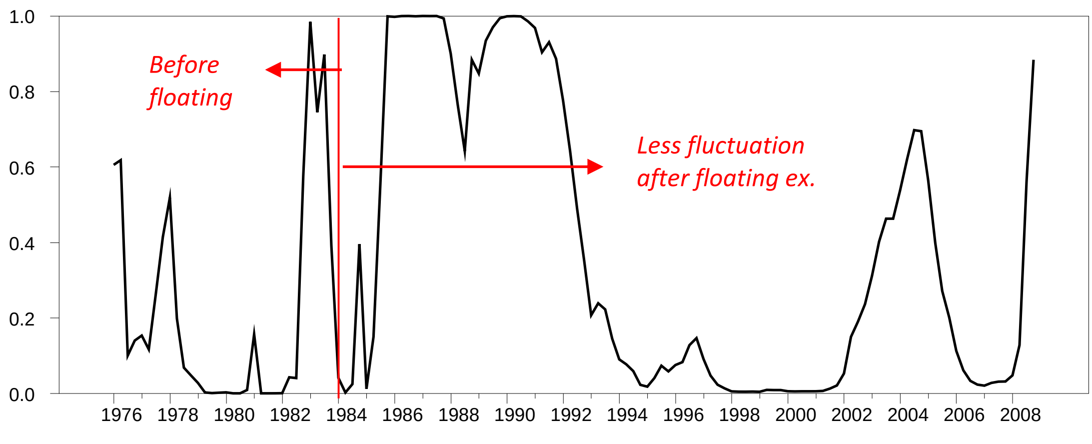
Column two of Table 6-11 and Table 6-12 shows the estimated parameters, with the interest rate difference used as the transition variable. The results show the coefficients of the output gap, interest rate difference and real exchange rate explain most of the nonlinearity. Figure 6-9 plots the transition function against the interest rate difference. In the figure, observations are distributed roughly equally between the left-hand and the right-hand tails of the logistic function, indicating smooth change between exchange rate regimes once interest rate differences go beyond the threshold level of 3.61%. Figure 6-10 is the plot of the estimated transition function over time. Similar to the plots of the UK and Sweden, frequent shifts between regimes and large changes in parameters have occurred mostly before Australia adopted the floating exchange rate system at the end of 1983. Diagnostic tests for normality, autocorrelation, ARCH effects, and constancy of coefficients presented in Table 6-13 suggest the model with dummy variables is well specified. Moreover, there is no evidence for any remaining nonlinearity of the STR-type.

**Figure 6-9 Estimated transition function as a function of the transition variable – Australia**




*Note:* figures display the plots of the estimated logistic transition functions, $G(.)$, against transition variables $s_t = i_{t-1} - \tilde{i}_{t-1}$.

**Figure 6-10 Estimated transition function over time - Australia**




*Note:* figures display the plots of the estimated logistic transition function, $G(.)$, over time with interest rate difference as the transition variable.

Overall, the nonlinear specification improves upon the linear one by explaining some of the variation in the exchange rate related to the extreme peaks of various transition variables. Figures of the transition functions over time indicate that transition between regimes with large changes in parameters occurred most frequently prior to the introduction of the floating exchange rate system and inflation targeting. This makes sense since our nonlinear Taylor type exchange rate relationships are based on Taylor rule interest rate models which are mainly used in studying the change and setting of monetary policy. As monetary policy has not greatly changed after the introduction of the floating system, so the same is the case with the exchange rate.

## 6.6 Out-of-sample Forecasting of STR models

Tests of out-of-sample forecasting performance are an alternative or complementary method to measure the usefulness of the model. It has been widely used as a way of evaluating estimated models, for example, Sarantis (1999) applies out-of-sample forecasting to examine the performance of nonlinear models to study the exchange rate, Brüggemann and Riedel (2011) use the same method in comparing the performance of interest rate reaction functions between linear and nonlinear models. Although the selected nonlinear models fit better than their linear counterparts, there is no guarantee that they will also provide better forecasts. Dijk et al. (2002) suggest that the general nonlinear models are superior to the linear ones in describing time series data, though it remains uncertain as to whether they have better forecasting ability. Moreover, it provides a useful aid in selecting among alternative exchange rate models. This is particularly true since linearity testing and estimation sometimes select different specifications. For example, in the above estimation, the linear test has shown the UK exchange rate follows an ESTR model when exchange volatility is taken as a transition variable. This is in conjunction with the estimation result, which has shown the nonlinear part is jointly insignificant. Therefore, the remaining section will focus on examining whether the kind of non-linearity captured by the STAR models provides some forecasting gains over the linear models and then come to a decision upon its posterior evaluation.

With regard to the previous literature, there are very few papers forecasting from the STAR models and their results are generally mixed. Sarantis (1999) applied the STAR model to forecasting real exchange rates and found STAR models do not consistently outperform linear models out-of-sample, though it outperforms the Markov regime switching model. Qin and Enders (2008) studied both the in-sample and out-of-sample fitting of the Taylor rule and their results showed that the LSTR models provide better forecasting performance than linear models during the period 1979Q3 to 1995Q4 when the criterion is the RMSE. However, during the period 1967Q1 to 1979Q2 and 1987Q4 to 2005Q4, the linear model performs better in forecasting. López-Suárez and Rodríguez-López (2011) studied the nonlinear behavior of the real exchange rate using smooth nonlinear error correction models and found nonlinear models provide higher out-of-sample forecasting precision than a random walk specification. Rapach and Wohar (2006) studied the out-of-sample forecasting performance of a nonlinear Band-TAR model and ESTAR model for the UK, Germany, France and Japan. Comparing these forecasting performances with a linear AR model by means of the MSPE, they found the nonlinear models offer some forecasting gain at longer horizons. However, the gains were not noticeable at shorter horizons.

Teräsvirta (2006) explains why nonlinear out-of-sample forecasting performance is no better than that of the linear model despite the fact that it may describe the given time series better than a linear model. He argues that a nonlinear model may not render better forecasts simply because nonlinear features are not present during the forecasting period. This is often the case when the forecasting period is short. Dijk et al. (2002) have suggested that the potential solution is a simulation based forecasting procedure. The detailed procedure will be discussed later in section 6.6.1. Another possible cause for the inferior forecasting performance of nonlinear models is that nonlinearity may be ‘spurious’. This is discussed by Clements and Hendry (1998). Nonlinearity may be present because there exists outliers or heteroscedasticity in a time series. In such a case, one may successfully estimate a nonlinear model for such time series, but the forecasting results may not improve comparatively to linear models. However we have already established above that the nonlinearities in our models are not due to the presence of outliers. Therefore, we expect our out-of-sample forecasting from nonlinear models to outperform the ones from linear models by applying the forecasting approach of Clements and Smith (1999).

### 6.6.1 Constructing and evaluating the forecasts

Forecasting with nonlinear models is more complicated than forecasting from linear models (Teräsvirta, 2006). In this study, we choose to generate forecasts by applying a simulation-based procedure (i.e. Monte Carlo method). This is also described in Clements and Smith (1999). The procedure to compute the out-of-sample forecasts is as follows.

Firstly, all models were re-estimated up to 1999Q4 and these estimates were used to generate a recursive forecasting for 2000Q1 to 2008Q4. Each out-of-sample forecast is constructed using all the data up to the forecasting period. So, in total, we will obtain 36 forecasts.

As noted in Clements and Smith (1997, 1999), we can write the nonlinear forecasting equation as:

$$\Delta s_{t+1} = g(\boldsymbol{X}_t; \theta) + \varepsilon_{t+1} \tag{6-22}$$

Assuming the error terms in this nonlinear model are Gaussian, we define the optimal forecast for $\Delta s_{t+h}$ at time $t$ is equal to the conditional mean:

$$\Delta s_{t+h|t} = E[\Delta s_{t+h}|\Omega] = E[g(\boldsymbol{X}_{t+h-1}; \theta)|\Omega] \tag{6-23}$$

where $\Omega$ is a set of past information. For a given set of $\boldsymbol{X}_t$, we simulate a realization for $\Delta s_{t+h}$ $(h \geq 1)$ by the 'Monte Carlo forecast' formula:

$$\Delta s_{t+h|t} = \frac{1}{N}\sum_{j=1}^{N} g(\boldsymbol{X}_{t+h,n};\theta) \tag{6-24}$$

where each $n$ value of $\varepsilon_{t+h}^{*}$ in $\boldsymbol{X}_{t+h,n}$ is a random draw from its standard normal distribution of residuals from the estimated model. We repeat the process 10000 times, this will give 10000 simulated realizations for $\Delta s_{t+h}$. The forecast of $\Delta s_{t+h}$ given $\boldsymbol{X}_{\boldsymbol{t}}$ is the mean of the 10000 simulated realizations. The Law of Large Numbers guarantees that the sample means converge to the true forecasts.

To evaluate the performance of our nonlinear model, we will compare these out-of-sample forecasts from nonlinear models with those from corresponding linear models. Moreover, a random walk which provides the benchmarks for all econometric exchange rate models will be used as a second benchmark.[82]

In the comparison exercise, we will first assess the out-of-sample forecasting performance in terms of the traditionally used mean squared forecast error (MSPE) criterion and Theil's U ratio. Models with smaller MSPE and Theil's U ratio have a better forecasting performance. Furthermore, in order to access whether the nonlinear model forecasts have superior predictive ability against the linear one, we perform the popular Clark and West (2007) (henceforth CW) test. All the test procedures are almost identical to the ones used in the linear model.[83] With respect to predictability tests of nonlinear models, Liu et al. (2010) have compared the power and size properties of the Diebold and Mariano (1995) and West (1996) (DMW) test with the CW test in a number of nonlinear models. Their results indicate the CW test is appropriately sized and has good power properties when applied to nonlinear models.

[82] The forecasting results for the linear and the random walk models are listed in chapter 5.

[83] The detailed procedures are described in Chapter 5 section 5.4.1.

### 6.6.2 Forecasting results

Table 6-15 to Table 6-17 present out-of-sample forecasting results for the UK, Sweden and Australia. The first column reports the MSPE obtained from our nonlinear models. The second and third columns present the Theil's U ratio with respect to the linear and the random walk models. The values are calculated as the ratio of the MSPE of the nonlinear model divided by the MSPE of the linear model/random walk. A number of less than one means that the non-linear model provides more accurate forecasts than the simple linear model or the random walk model. The last two columns show the CW statistics with respect to the two benchmarks. The values leading to a rejection of the null hypothesis of equal forecasting accuracy are indicated with asterisks.

Focusing on these forecasting results, it is quite interesting to note that in terms of both the MSPE criteria and CW statistics, the nonlinear STAR models significantly outperform both the linear model and the random walk model at every specification which passes the nonlinearity test. Moreover, the previous argument that the linear forecasting performance is no worse or even better than the nonlinear models has also been rejected. In general, our results across exchange rates show nonlinear STR models have a better predictive ability than the linear Taylor rule models and can improve over the forecasting accuracy of linear econometric models.

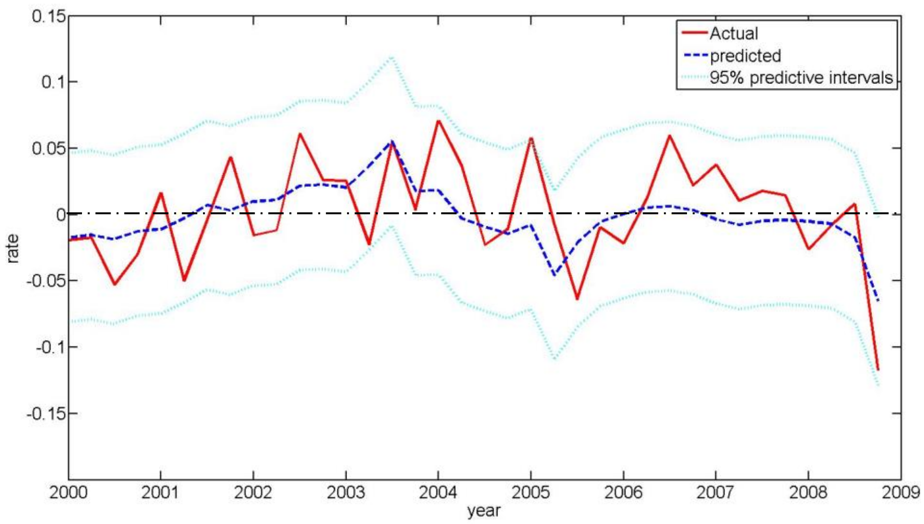
For the UK data, the forecasting results in general confirm those of Rapach and Wohar (2006), with nonlinear models dominating the linear models in forecasting the exchange rate change with respect to all criterions. Note that all these measures can lead to a ranking of the competing models according to their forecasting performance. With regard to the UK, the ranking provided by both criterions are consistently pointing to the STR model with the interest rate difference as the transition variable offering the best forecasting performance.

**Table 6-15 out-of-sample forecast result - UK**

| | *MSPE* | *Theil's U (linear model)* | *Theil's U (random walk)* | *CW (linear model )* | *CW (random walk)* |
|---|---|---|---|---|---|
| $\boldsymbol{i_{t-1} - \tilde{i}_{t-1}}$ | 0.000985 | 0.661518 | 0.724265 | 2.723** | 2.047** |
| $\boldsymbol{y_t - \tilde{y}_t}$ | 0.001252 | 0.840833 | 0.920588 | 1.565* | 1.712** |
| $\boldsymbol{w_t - \tilde{w}_t(s)}$ | 0.001307 | 0.877770 | 0.961029 | 1.318* | 2.158** |
| $\boldsymbol{\tilde{q}_t}$ | 0.001090 | 0.732035 | 0.801471 | 2.425** | 1.791** |
| ***volatility*** | 0.001044 | 0.701142 | 0.767647 | 2.442** | 2.527** |

*Note:* each forecast is obtained as the average over 10,000 replications. Theil's U and CW are test values relative to the benchmark of the random walk and linear models, respectively. Significance levels at 90% and 95%, are denoted by one and two stars, respectively. For Theil's U, a value less than one implies nonlinear model performs better. For CW statistics, the null hypothesis of equal predictability is rejected if the statistic is greater than $+1.282$ (for a one side 0.10 test) or $+1.645$ (for a one side 0.05 tests). The random walk MSPE: 0.001360. The linear model MSPE: 0.001489.

**Figure 6-11 Figure of forecasting and actual exchange rate changes – UK**




*Note*: these graphs show forecasts achieved from the LSTR models with interest rate as transition variable for the dollar against the Australia dollar. Exchange rate are defined as the U.S. price per unit of foreign currency. Since results based on different models are similar, to conserve space, only results for the most successful specification are reported here. The line at zero represent forecast of a random walk.

Figure 6-11 provides a graphical representation of how well the forecasting from our nonlinear model tracks the actual exchange rate change. This is the case when interest rate differences are the transition variable. The lower and upper dotted lines represent the 95% prediction interval of the forecast. According to this figure, the nonlinear STR model was able to produce reliable forecasts of the exchange rate changes up to the last quarter of 2008. Most actual changes in the exchange rate within the forecasting period lie within 95% of the predictive intervals. However, the reliability of our nonlinear forecasts breaks down by the end of 2008. However, given the unprecedented world economic turmoil unleashed by the events in the U.S. financial system during September 2008, this is not surprising.

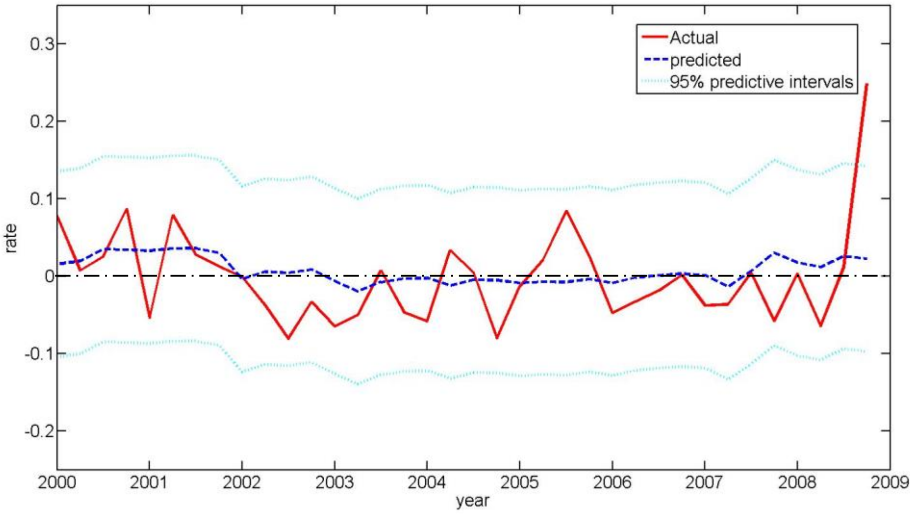
Table 6-16 shows the forecasting results for Sweden's exchange rate changes. With the four different specifications all performing better in the forecasting when compared to a linear or the random walk model in terms of the MSPE, the ESTR model with house price differences acting as the transition variable provides better forecasts than other specifications. Its forecasts present the smallest MSPE and largest CW statistic.

**Table 6-16 out-of-sample forecasting result - Sweden**

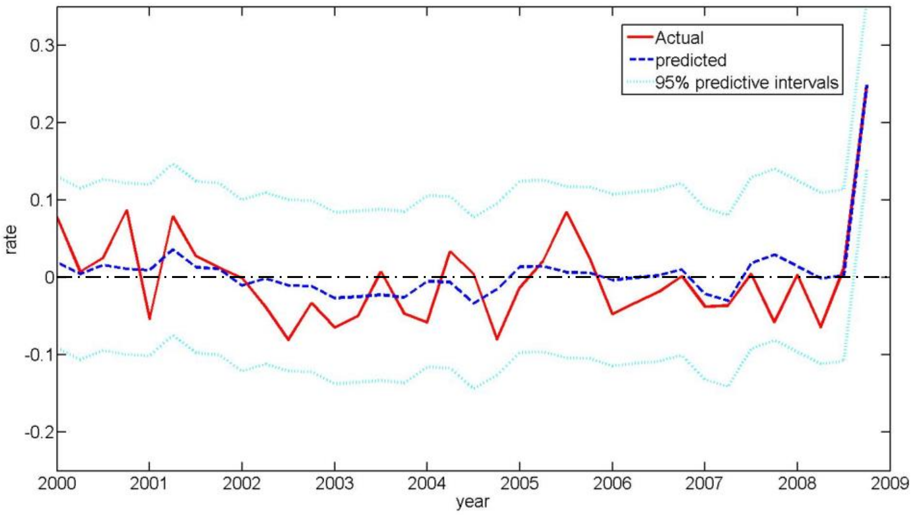
| | *MSPE* | *Theil's U (linear model)* | *Theil's U (random walk)* | *CW (linear model)* | *CW (random walk)* |
|---|---|---|---|---|---|
| $\boldsymbol{i_{t-1} - \tilde{i}_{t-1}}$ | 0.003494 | 0.963331 | 0.908713 | 1.389* | 1.570* |
| $\boldsymbol{\pi_t - \tilde{\pi}_t}$ | 0.003367 | 0.928315 | 0.875683 | 2.017** | 2.328** |
| $\boldsymbol{w_t - \tilde{w}_t(h)}$ | 0.002987 | 0.823546 | 0.776853 | 2.608** | 2.470** |
| ***volatility*** | 0.003029 | 0.835125 | 0.787776 | 2.279** | 2.213** |

*Note:* each forecast is obtained as the average over 10,000 replications. Theil's U and CW are test values relative to the benchmark of the random walk and linear models, respectively. Significance levels at 90% and 95%, are denoted by one and two stars, respectively. For Theil's U, a value less than one implies nonlinear model performs better. For CW statistics, the null hypothesis of equal predictability is rejected if the statistic is greater than $+1.282$ (for a one side 0.10 test) or $+1.645$ (for a one side 0.05 tests). The random walk MSPE: 0.003845.The linear model MSPE: 0003627.

**Figure 6-12 Graph of forecasting and actual exchange rate changes - Sweden**




(a). transition variable: interest rate difference




(b). transition variable: house price difference

*Note*: these graphs show forecasts achieved from the LSTR and ESTR model with interest rate difference and house price difference as transition variable, respectively, for the dollar against the Swedish krona. Exchange rate are defined as the U.S. price per unit of foreign currency. Since results based on different models are similar, to conserve space, only results for the most successful specification are reported here. The line at zero represent forecast of a random walk.

Figure 6-12(b) shows the figure of the actual and forecast exchange rate with the wealth effect being the transition variable. In this case, we found that the forecast exchange rate has been closely following the actual changes.

In contrast, the LSTR model with the interest rate difference as the transition variable is not superior to the linear model. Also, the CW statistics are significant only at the 10% level. However, it still yields superior forecasts over the linear models. Based on Figure 6-12(a), we observe that the results are not as good as the ESTR model when the house price difference is used as the transition variable, but all actual exchange rate changes are lying within the 95% predictive interval apart from the last quarter of 2008 which again is the start of financial crisis.

For Australia, the results show that the only transition functions giving strong evidence of nonlinearity in the adjustment of the exchange rate are the interest rate difference. Therefore, we will focus on the forecasting result of a LSTR model with interest rate differences acting as the transition variable. Both MSPE and CW criterions indicate a superior forecasting performance of the LSTR model over both the simple random walk and a linear Taylor rule model. By examining Figure 6-13, we see that forecasting from the LSTR model approaches the actual changes in the exchange rate relatively closely apart from at the end of the testing period. Based on the above result, we conclude that the nonlinear LSTR model with interest rate differences as the transition variable provide better forecasts than a linear model.

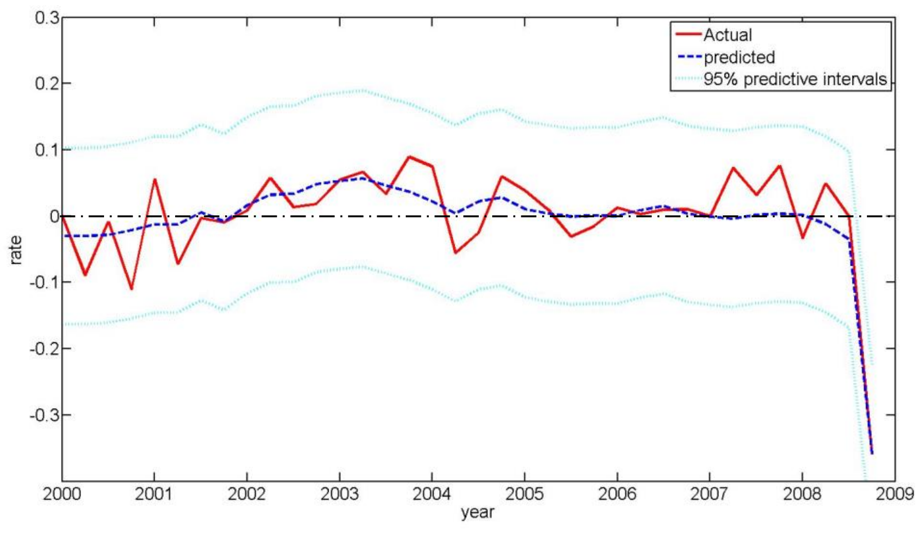
In addition, we present forecasting results for specifications (1) and (3) (i.e. the real exchange rate or the output gap used as the transition variable). Previous results indicate that the nonlinearity in these two cases was due to the result of unusually large residuals. For the forecasting, we find that although the nonlinear models have smaller MSPE statistics compared to a random walk and the linear model, the apparent predictive advantage over the linear model is not significant in terms of the CW test. This is consistent with results from the estimation. The nonlinear STR models do not provide much of a gain over the linear models in forecasting exchange

**Table 6-17 out-of-sample forecasting result - Australia**

| | ***MSPE*** | ***Theil's U (linear model)*** | ***Theil's U (random walk)*** | ***CW (linear model)*** | ***CW (random walk)*** |
|---|---|---|---|---|---|
| $\boldsymbol{i_{t-1} - \tilde{i}_{t-1}}$ | 0.003609 | 0.612110 | 0.619464 | 1.836** | 1.653** |
| $\boldsymbol{y_t - \tilde{y}_t}$ | 0.003159 | 0.535787 | 0.542225 | 1.293* | 1.302* |
| $\boldsymbol{\tilde{q}_t}$ | 0.002930 | 0.496947 | 0.502918 | 1.179 | 1.221 |

*Note:* each forecast is obtained as the average over 10,000 replications. Theil's U and CW are test values relative to the benchmark of the random walk and linear models, respectively. Significance levels at 90% and 95%, are denoted by one and two stars, respectively. For Theil's U, a value less than one implies nonlinear model performs better. For CW statistics, the null hypothesis of equal predictability is rejected if the statistic is greater than $+1.282$ (for a one side 0.10 test) or $+1.645$ (for a one side 0.05 tests). The random walk MSPE: 0.005826. The linear model MSPE: 0.005896.

**Figure 6-13 Graph of forecasting and actual exchange rate changes - Australia**




*Note*: these graphs show forecasts achieved from the LSTR models with interest rate as transition variable for the dollar against the Australia dollar. Exchange rate are defined as the U.S. price per unit of foreign currency. Since results based on different models are similar, to conserve space, only results for the most successful specification are reported here. The line at zero represent forecast of a random walk.

rate accuracy when either the output gap or real exchange rate are the transition variables.

Combining all the evidence in Figure 6-11 to Figure 6-13, we found that the nonlinear STR model failed to predict the world economic turmoil at the end of 2008. Despite that, it appears that the out-of-sample predictive performance of the STR models improves upon the linear models for all the countries studied. On the basis of these forecasting results, one can make a strong case in favour of the STR models.

## 6.7 Conclusion

In this chapter, we have investigated the possibility of non-linear mechanisms within the Taylor rule type exchange rate models. The family of smooth transition regression models have been used as the main modelling technique. Using quarterly data on dollar-sterling, dollar-Swedish krona and dollar-Australian exchange rates between 1975 and 2008, We found strong evidence of nonlinearities in the exchange rate with respect to several macroeconomic determinants. Therefore, linear relationships for the Taylor rule exchange rates models can be improved by considering the regime changes.

The existence of nonlinearities varies for different transition variables and is estimated in different forms of smooth transition specifications for different countries. In general, the interest rate differential is found to be the most important source of nonlinearities in exchange rates for all the countries studied. For both the UK and Australia, the Logistic STR model with interest rate differences as the transition variable are well specified and prevail over other nonlinear models. Whereas for Sweden’s exchange rate, the estimation results based on the wealth effect as the transition variable generally give a better interpretation. Furthermore, using the same method applied by Sarantis (1999), we identify the nature of the nonlinearity and found none of the nonlinearities are due to the presence of outliers in the economic data.

In the out-of-sample analysis, we chose the driftless random walk and linear Taylor rule as our benchmark models. Results in general show that the predictive performance of the STR models improves upon its linear specification for all the countries studied. On the basis of these forecasting results, one can make a strong case in favour of the STR models.

This study mainly uses point forecasting in conducting out-of-sample forecasts. Further research could focus on testing out-of-sample performance by using different criteria, for example, density forecasts. Since STR models provide smooth transition between regimes, an evaluation based on density forecasts may reveal greater discrimination over the transition process and better exploit the forecasting gains of the STR models.

# Chapter 7 Conclusion

## 7.1 Importance of the study and Policy implications

Since inflation targeting was introduced in the 1990s, the Taylor rule has become the dominant approach to determining interest rates and monetary policy in general. Within the literature there is a strand which argues for the inclusion of wealth measures within the Taylor rule and monetary policy in general, with Castro and Sousa (2012) providing evidence of the importance of wealth in determining monetary policy. Various studies have analysed the relationship between wealth effects and exchange rates, such as Smith (1992) and Granger et al. (2000). Overall, most of the results show changes in stock prices have significant effects on the exchange rate, using a variety of different exchange rate models. However, some like Case et al. (2005) suggest both stock price and house price have varying degrees of influence on the macro economy, with housing being the most significant. Given the importance of the exchange rate to the economy as a whole, especially in the conduct of monetary policy, it is important to understand what factors determine its movements and how it interacts with other financial markets.

As yet, there has been no attempt to use the Taylor rule framework to investigate the relationship between asset prices and exchange rate models. This study combines two areas of the existing literature, where various wealth effects have been included into the Taylor rule and also where wealth effects have been added to exchange rate models, to improve the model and increase its forecasting performance. Following the financial crisis, financial markets have become more integrated, including the foreign exchange and equity markets. This study adds to the evidence of an increasing relationship between these markets, identified initially by Solnik (1987) as capital controls have been reduced throughout the 1980s and 1990s.

On the other hand, this thesis provides a comprehensive study of both the in-sample and out-of-sample properties of the Taylor rule exchange rate model. In total, we have studied sixteen different specifications of the Taylor rule exchange rate. Both linear and nonlinear techniques have been employed with results compared. A number of techniques have been used to get the most accurate estimation and forecasting results. Following the discussion in section 2.5.4. the data revision problems when determining the output gap have been taken into account, such that real time data are used in estimating the output gap in order to analyse the behaviour of the monetary authorities' in formulating policy. This real time output gap measurement is also applied in constructing the exchange rate forecasts. In order to test the forecasting performance, a number of criteria have been used. A discussion about the most appropriate tests for equal predictive accuracy of nested models is also found in section 5.3. Furthermore, Different forecasting windows have been used in order to study exchange rate movements during different periods (see section 5.5.3).

## 7.2 Main Results and Contributions

The main focus is on assessing the connection between exchange rate determination and the traditional Taylor rule model with asset prices in representing wealth effects. Based on the model of Molodtsova and Papell (2009), I have contributed to the growing literature on the relationship between asset markets and the macro economy, especially the exchange rate, by showing that the predictability of the three exchange rate can be improved by the inclusion of asset prices.  This evidence of improved predictability are found in both linear and non-linear forecasts. The first three chapters have served as cornerstones for this research. Within these chapters, I have made a review on the development of exchange rate models. Including their ability to forecast the exchange rate as well as a discussion on the exchange rate regimes and policies for each studied country.

The first empirical chapter (Chapter 4) focuses on an alternative specification of a conventional Taylor rule exchange rate model. As yet there has been no attempt to use the Taylor rule framework to investigate the relationship between wealth effects and exchange rate models, this has been done with other versions of models of exchange rate determination. We contribute to the recent literature by incorporating equity wealth and housing wealth into the standard Taylor rule model and estimated using a variant of the Taylor rule based exchange rate model. In general, I found that where a wealth effect has been added, the estimation results have been improved. However, it is difficult to decide whether it is house prices or stock prices which consistently provide the better measure of exchange rate movements. Overall, we found models with stock prices being the most appropriate in the UK and Australia, whilst house prices appear better in explaining exchange rate movements for Sweden. In addition, I found the results are sensitive to the specification of the model with the better results coming from the models with the restricted coefficients in general. The coefficients signs and magnitudes vary across different models. This conforms with the assumption suggested by Molodtsova et al. (2008). Moreover, by analysing the time series properties of the Taylor rule exchange rate models, we found that variables commonly used in such modelling are likely to be integrated of order one or near integrated. With reference to the background information in Chapter 3, we found most of these break dates can be explained by changes in exchange rate regimes or monetary policies in these countries. By accounting for structural breaks, almost all variables become stationary.

Chapter 5 examines the performance of the Taylor rule based models in terms of out-of-sample forecasting performance. As with much of the literature, the best test of a model is the out-of-sample forecast relative to that of the random walk. The out-of-sample forecasts of the Taylor rule exchange rate model with a wealth effect overall outperform the standard Taylor rule based model without the wealth effect and in some cases the random walk. However as with the Meese and Rogoff (1983) study, it fails to outperform the random walk consistently across countries and particularly across models. The inclusion of wealth effects into this model provides evidence of their importance in determining exchange rates, which has also been apparent in other models including stock prices. Moreover, taking the USD/Australia exchange rate as an example, we investigate the forecasting performance over different windows. Stronger evidence of predictability at one-quarter-ahead horizons is found when estimating the model using data after Australia allowed free-floating of its exchange rate. This result confirms the criticism of Rogoff and Stavrakeva (2008) and Rossi and Inoue (2012) in the sense that the robustness of out-of-sample predictability depends on the choice of window size, especially in the presence of structural breaks.

Chapter 6 explored the nonlinearity in the relationship between exchange rates and Taylor rule fundamentals. The STR family of models has been used to explore the nonlinear dependency. In general, we found the existence of nonlinearities varies for different transition variables and therefore requires the model to be estimated with different forms of smooth transition specifications for different countries. Overall, the interest rate differential is found to be the most important source of nonlinearities in exchange rates for all the countries studied. For both the UK and Australia, the Logistic STR model with interest rate differences as the transition variable are well specified and prevail over other nonlinear models. Whereas for Sweden's exchange rate movements, the estimation results based on the wealth effect as the transition variable generally give a better interpretation. Furthermore, using the same method as Sarantis (1999), we found none of the nonlinearities are due to the presence of outliers in the economic data. In the out-of-sample analysis, we chose the driftless random walk and linear Taylor rule as our benchmark models. Results in general show that predictive performance of the STR models improves upon its linear specification for all the countries studied. In addition, it was found that the transition function is able to capture several major exchange rate movements for these countries. Changes in parameter values occurred more frequently prior to the introduction of the floating exchange rate system and inflation targeting. Since monetary policy did not changed much after the introduction of the floating system, so does the same case with the exchange rate movement. Overall, as with previous literature on exchange rates, nonlinear models provide more supportive results when studying the exchange rate puzzles and performed well in out-of-sample forecasting tests.

## 7.3 Future Research

In Chapter 4, we have discussed that there are various detrending methods for estimating potential output. The most commonly used detrending methods include linear, quadratic and Hodrick-Prescott (1997) (HP). In this study, the HP filter is chosen. This is mainly because the studies by Molodtsova and Papell (2009) and others have shown that output gap derived from the HP filter generates better forecasting results than the other two.

All these previous study have tested the performance of different detrending techniques by comparing their forecasting or estimating results. However, in recent studies of Nikolsko-Rzhevskyy et al. (2014), and Nikolsko-Rzhevskyy et al. (2013), the Okun's Law has been used as benchmark in comparing different estimation of real-time output gaps. Okun's law states that the output gap equals a (negative) coefficient times the difference between current unemployment and the natural rate of unemployment. Based on real-time U.S. data, they found some different result from the previous literature. They show neither linear nor HP detrended real-time output gaps are a good metric for the U.S., but the quadratic detrended output gap are better. Therefore, it may be worthwhile to investigate whether the same results will apply to quasi-real time detrending or to the other countries in this study.

Secondly, due to data limitations this thesis studies exchange rates based on only three countries, all of them are small open economies with highly developed asset markets. Recent studies on emerging countries found that the Taylor rule is also useful in studying central bank behavior, especially for emerging countries following an inflation targeting approach (e.g. Taylor, 2000; Galimberti and Moura, 2013). Although, some modifications may be required in order to capture certain features of emerging economies, future studies could test whether central banks of emerging economies respond to changes in exchange rates, and study exchange rate movement by applying this type of policy rule. Due to the limited data available in these countries the analysis could be carried out based on a panel data set.

Thirdly, studies on the Taylor rule exchange rate use quarterly data with forecast horizons of one quarter ahead. As Cheung, Chinn, and Pascual (2005) state, exchange rate movements are sensitive to the choice of time horizon, forecast window, forecast horizon, specific exchange rates, different benchmark and other factors. In this study, we only tested Australia for different forecast periods and used the popular benchmark of the random walk together with the Taylor rule model without wealth effects. It may be worth to investigating the difference in results under other different criteria.

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# Appendix I: Critical value for Lee-Strazicich tests

### Critical Values of the One-Break Minimum $LM_\tau$ Test

**Model A**

| 1% | 5% | 10% |
|---|---|---|
| -4.239 | -3.566 | -3.211 |

**Model C**

| λ | 1% | 5% | 10% |
|---|---|---|---|
| **.1** | -5.11 | -4.50 | -4.21 |
| **.2** | -5.07 | -4.47 | -4.20 |
| **.3** | -5.15 | -4.45 | -4.18 |
| **.4** | -5.05 | -4.50 | -4.18 |
| **.5** | -5.11 | -4.51 | -4.17 |

Note: All critical values were derived in samples of size T=100. Critical values in Model C (intercept and Trend Break) depend (somewhat) on the location of the break ($\lambda = T_B/T$) and the symmetric around $\lambda$ and $(1-\lambda)$. Model C critical values at additional break locations can be interpolated.

### Critical Values of the Endogenous Two-Break Minimum Tests (T=100)

**(I) Model A**

| | 1% | 5% | 10% |
|---|---|---|---|
| $LM_\tau$ | -4.545 | -3.842 | -3.504 |
| $LM_\rho$ | -35.73 | -26.89 | -22.89 |
| $LP_t$ | -6.420 | -5.913 | -5.587 |
| $LP_t^*$ | -6.400 | -5.853 | -5.560 |

Note: the DGP in the simulation does not include breaks. The LP tests are affected by breaks, while LM tests are invariant to breaks in Model A.

### (II) Model C (I)

| | 1% | 5% | 10% |
|---|---|---|---|
| $\boldsymbol{LM_\tau}$ | **-5.825** | **-5.286** | **-4.989** |
| $\boldsymbol{LM_\rho}$ | **-52.551** | **-45.532** | **-41.664** |
| $\boldsymbol{LP_t}$ | **-6.936** | **-6.386** | **-6.108** |
| $\boldsymbol{LP_t^*}$ | **-6.945** | **-6.344** | **-6.064** |

Note: the DGP in simulation does not include breaks. Both LP and LM tests are affected by breaks in Model C.

### (III) Model C (II)

#### (i) $\boldsymbol{LM_\tau}$

| $\lambda_1$ | $\lambda_2$ | | |
|---|---|---|---|
| | .4 | .6 | .8 |
| .2 | -6.16, -5.59, -5.28 | -6.40, -5.74, -5.32 | -6.33, -5.71, -5.33 |
| .4 | - | -6.46, -5.67, -5.31 | -6.42, -5.65, -5.32 |
| .6 | - | - | -6.32, -5.73, -5.32 |

#### (ii) $\boldsymbol{LM_\rho}$

| $\lambda_1$ | $\lambda_2$ | | |
|---|---|---|---|
| | .4 | .6 | .8 |
| .2 | -55.5, -47.9, -44.0 | -58.6, -50.0, -44.4 | -57.6, -49.6, -44.6 |
| .4 | - | -59.3, -49.0, -44.3 | -58.8, -48.7, -44.5 |
| .6 | - | - | -57.5, -49.8, -44.4 |

Note: Critical values are at 1%, 5% and 10% levels, respectively

## Appendix II: Estimation of Taylor rule exchange rate models (without wealth effect factors)

| *Asymmetric with smoothing, heterogeneous coefficient* | | | | | | |
|---|---|---|---|---|---|---|
| | ***US UK*** | | ***US SD*** | | ***US AUS*** | |
| ***Variable*** | ***Coefficient*** | ***t-Statistic*** | ***Coefficient*** | ***t-Statistic*** | ***Coefficient*** | ***t-Statistic*** |
| $c$ | 0.099400 | 3.397300* | -0.033413 | -2.591737* | -0.037401 | -1.492929 |
| $\pi_t$ | 1.090867 | 2.247718* | 0.715719 | 1.759921* | 0.39256 | 0.796267 |
| $\tilde{\pi}_t$ | -0.525904 | -2.299041* | -0.511958 | -2.205619* | 0.101749 | 0.38776 |
| $y_t$ | -0.164055 | -0.303366 | -0.209456 | -0.372686 | 0.182636 | 0.294353 |
| $\tilde{y}_t$ | 0.923487 | 1.670845** | -0.1342 | -0.441793 | -0.153984 | -0.410287 |
| $\tilde{q}_t$ | -0.192434 | -3.341633* | 0.099617 | 1.095801 | -0.096806 | -1.881851** |
| $i_{t-1}$ | -0.006348 | -2.523782* | -0.0003 | -0.11088 | -0.003479 | -1.10211 |
| $\tilde{i}_{t-1}$ | 0.003035 | 1.452825 | 0.004226 | 2.260203* | 0.000304 | 0.141296 |
| ***Adj. R-squared*** | 0.085887 | | 0.081814 | | 0.006431 | |

*Note*: table show coefficient and t statistics of the variable over the entire sample period. Models are estimated by OLS where standard errors have been Newey-West corrected. *and **means significance at 5% and 1% significant level, respectively.

| *Asymmetric with smoothing, homogeneous coefficient* | | | | | | |
|---|---|---|---|---|---|---|
| | ***US UK*** | | ***US SD*** | | ***US AUS*** | |
| ***Variable*** | ***Coefficient*** | ***t-Statistic*** | ***Coefficient*** | ***t-Statistic*** | ***Coefficient*** | ***t-Statistic*** |
| $c$ | 0.062772 | 2.061748* | 0.001433 | 0.248314 | -0.026765 | -2.530152* |
| $\tilde{\pi}_t - \pi_t$ | -0.325064 | -1.661101** | -0.22823 | -0.954102 | 0.015652 | 0.058503 |
| $\tilde{y}_t - y_t$ | 0.475656 | 0.880256 | -0.182723 | -0.546988 | -0.121175 | -0.296707 |
| $\tilde{q}_t$ | -0.120038 | -2.239726* | 0.148849 | 1.576299 | -0.069534 | -1.931351** |
| $\tilde{i}_{t-1} - i_{t-1}$ | 0.002217 | 1.070451 | 0.00261 | 1.200786 | 0.000117 | 0.05551 |
| ***Adj. R-squared*** | 0.056438 | | 0.016780 | | 0.008373 | |

*Note*: table show coefficient and t statistics of the variable over the entire sample period. Models are estimated by OLS where standard errors have been Newey-West corrected. *and **means significance at 5% and 1% significant level, respectively.

| Symmetric with smoothing, heterogeneous coefficient | | | | | | |
|---|---|---|---|---|---|---|
| | US UK | | US SD | | US AUS | |
| Variable | Coefficient | t-Statistic | Coefficient | t-Statistic | Coefficient | t-Statistic |
| $c$ | 0.006824 | 0.597868 | -0.03677 | -2.782408* | 0.007066 | 0.547606 |
| $\pi_t$ | 0.190103 | 0.416884 | 0.739448 | 1.632253** | -0.057265 | -0.119027 |
| $\tilde{\pi}_t$ | -0.151806 | -0.694822 | -0.495784 | -2.016487* | 0.13583 | 0.501409 |
| $y_t$ | 0.078852 | 0.141211 | -0.223924 | -0.370564 | 0.301601 | 0.508547 |
| $\tilde{y}_t$ | 0.185525 | 0.36227 | -0.220857 | -0.724684 | -0.320614 | -0.857707 |
| $i_{t-1}$ | -0.003294 | -1.151022 | -0.0001 | -0.03575 | -0.002218 | -0.665389 |
| $\tilde{i}_{t-1}$ | 0.001488 | 0.60215 | 0.004356 | 2.284173* | -0.000325 | -0.155509 |
| Adj. R-squared | -0.013581 | | 0.080147 | | -0.025043 | |

*Note*: table show coefficient and t statistics of the variable over the entire sample period. Models are estimated by OLS where standard errors have been Newey-West corrected. *and **means significance at 5% and 1% significant level, respectively.

| Symmetric with smoothing, homogeneous coefficient | | | | | | |
|---|---|---|---|---|---|---|
| | US UK | | US SD | | US AUS | |
| Variable | Coefficient | t-Statistic | Coefficient | t-Statistic | Coefficient | t-Statistic |
| $c$ | -0.003307 | -0.580508 | 0.001517 | 0.237045 | -0.00698 | -1.145195 |
| $\tilde{\pi}_t - \pi_t$ | -0.178548 | -0.967068 | -0.143244 | -0.549187 | 0.041649 | 0.150084 |
| $\tilde{y}_t - y_t$ | 0.102947 | 0.235254 | -0.273583 | -0.779661 | -0.275544 | -0.657025 |
| $\tilde{i}_{t-1} - i_{t-1}$ | 0.00192 | 0.794362 | 0.002647 | 1.1045 | 0.000511 | 0.267737 |
| Adj. R-squared | -0.000085 | | 0.008408 | | -0.016398 | |

*Note*: table show coefficient and t statistics of the variable over the entire sample period. Models are estimated by OLS where standard errors have been Newey-West corrected. *and **means significance at 5% and 1% significant level, respectively.

| Asymmetric with no smoothing, heterogeneous coefficient | | | | | | |
|---|---|---|---|---|---|---|
| | US UK | | US SD | | US AUS | |
| Variable | Coefficient | t-Statistic | Coefficient | t-Statistic | Coefficient | t-Statistic |
| $c$ | 0.078691 | 2.359279* | -0.010978 | -1.266687 | -0.041167 | -1.443143 |
| $\pi_t$ | 0.594697 | 1.263739 | 0.494853 | 1.475316 | 0.183915 | 0.507125 |
| $\tilde{\pi}_t$ | -0.449411 | -1.864908** | -0.120482 | -0.581594 | -0.032694 | -0.1358 |
| $y_t$ | -0.39029 | -0.568046 | -0.164681 | -0.305823 | -0.151723 | -0.176148 |
| $\tilde{y}_t$ | 0.883446 | 1.514437 | -0.326225 | -0.86129 | -0.040969 | -0.087135 |
| $\tilde{q}_t$ | -0.152872 | -2.455457* | 0.133623 | 1.822671* | -0.094046 | -1.60963 |
| Adj. R-squared | 0.051379 | | 0.024598 | | 0.005544 | |

*Note*: table show coefficient and t statistics of the variable over the entire sample period. Models are estimated by OLS where standard errors have been Newey-West corrected. *and **means significance at 5% and 1% significant level, respectively.

| *Asymmetric with no smoothing, homogeneous coefficient* | | | | | | |
|---|---|---|---|---|---|---|
| | ***US UK*** | | ***US SD*** | | ***US AUS*** | |
| ***Variable*** | ***Coefficient*** | ***t-Statistic*** | ***Coefficient*** | ***t-Statistic*** | ***Coefficient*** | ***t-Statistic*** |
| $c$ | 0.065324 | 2.117512* | 0.00479 | 0.949245 | -0.026104 | -2.255808* |
| $\tilde{\pi}_t - \pi_t$ | -0.347097 | -1.783758** | -0.074108 | -0.396427 | 0.031165 | 0.141952 |
| $\tilde{y}_t - y_t$ | 0.559816 | 1.011262 | -0.214155 | -0.614897 | -0.116058 | -0.283953 |
| $\tilde{q}_t$ | -0.117898 | -2.166027* | 0.153735 | 1.93** | -0.068315 | -2.031083* |
| ***Adj. R-squared*** | 0.051233 | | 0.000732 | | 0.015032 | |

*Note*: table show coefficient and t statistics of the variable over the entire sample period. Models are estimated by OLS where standard errors have been Newey-West corrected. *and **means significance at 5% and 1% significant level, respectively.

| *Symmetric with no smoothing, heterogeneous coefficient* | | | | | | |
|---|---|---|---|---|---|---|
| | ***US UK*** | | ***US SD*** | | ***US AUS*** | |
| ***Variable*** | ***Coefficient*** | ***t-Statistic*** | ***Coefficient*** | ***t-Statistic*** | ***Coefficient*** | ***t-Statistic*** |
| $c$ | 0.004701 | 0.480625 | -0.012126 | -1.257843 | -0.00069 | -0.067958 |
| $\pi_t$ | 0.024165 | 0.057357 | 0.445787 | 1.276463 | -0.143975 | -0.462462 |
| $\tilde{\pi}_t$ | -0.148423 | -0.688947 | -0.043719 | -0.204282 | 0.034783 | 0.140111 |
| $y_t$ | -0.110176 | -0.177211 | -0.113214 | -0.192942 | 0.07529 | 0.106322 |
| $\tilde{y}_t$ | 0.23077 | 0.469123 | -0.412097 | -1.011255 | -0.303566 | -0.802156 |
| ***Adj. R-squared*** | -0.015540 | | 0.016038 | | -0.019649 | |

*Note*: table show coefficient and t statistics of the variable over the entire sample period. Models are estimated by OLS where standard errors have been Newey-West corrected. *and **means significance at 5% and 1% significant level, respectively.

| *Symmetric with no smoothing, homogeneous coefficient* | | | | | | |
|---|---|---|---|---|---|---|
| | ***US UK*** | | ***US SD*** | | ***US AUS*** | |
| ***Variable*** | ***Coefficient*** | ***t-Statistic*** | ***Coefficient*** | ***t-Statistic*** | ***Coefficient*** | ***t-Statistic*** |
| $c$ | -4.96E-05 | -0.01076 | 0.004813 | 0.867306 | -0.005985 | -0.940121 |
| $\tilde{\pi}_t - \pi_t$ | -0.196313 | -1.095479 | 0.019139 | 0.099773 | 0.075797 | 0.351441 |
| $\tilde{y}_t - y_t$ | 0.18257 | 0.415611 | -0.305127 | -0.81604 | -0.271085 | -0.65211 |
| ***Adj. R-squared*** | -0.002768 | | -0.007354 | | -0.009181 | |

*Note*: table show coefficient and t statistics of the variable over the entire sample period. Models are estimated by OLS where standard errors have been Newey-West corrected. *and **means significance at 5% and 1% significant level, respectively.

# Appendix III: Result from linear estimation

### Table III-1: Estimation results from the linear model – UK

| *Model 3*<br>*Asymmetric with smoothing, homogeneous coefficient with stock* | | |
|---|---|---|
| ***Variable*** | ***Coefficient*** | ***t-Statistic*** |
| $\boldsymbol{c}$ | 0.055995 | 2.047277* |
| $\boldsymbol{\tilde{\pi}_t - \pi_t}$ | -0.285568 | -1.463864 |
| $\boldsymbol{\tilde{y}_t - y_t}$ | 0.597995 | 1.196757 |
| $\boldsymbol{\tilde{q}_t}$ | -0.112318 | -2.401056* |
| $\boldsymbol{\tilde{\imath}_{t-1} - i_{t-1}}$ | 0.00333 | 1.850639** |
| $\boldsymbol{\tilde{w}_t - w_t(S)}$ | 0.186135 | 2.743348* |
| ***R-squared*** | 0.1423 | |
| $\boldsymbol{adj. R^2}$ | 0.109 | |
| $\boldsymbol{\hat{\sigma}}$ | 0.0488 | |
| ***Log likelihood*** | 217.252 | |

*Note:* model is estimated using OLS with Newey-West corrected standard error. $adj. R^2$ is the adjusted $R^2$ . $\hat{\sigma}$ is the standard errors of regression. * and ** denote significant at the 5% and 10% level, respectively.

### Table III-2: Estimation results from the linear model - Sweden

| *Model 4*<br>*Asymmetric with smoothing, homogeneous coefficient with house* | | |
|---|---|---|
| ***Variable*** | ***Coefficient*** | ***t-Statistic*** |
| $\boldsymbol{c}$ | 0.001809 | 0.287926 |
| $\boldsymbol{\tilde{\pi}_t - \pi_t}$ | -0.308850 | -0.982780 |
| $\boldsymbol{\tilde{y}_t - y_t}$ | -0.611430 | -1.72622** |
| $\boldsymbol{\tilde{q}_t}$ | -0.124017 | 1.329107 |
| $\boldsymbol{\tilde{\imath}_{t-1} - i_{t-1}}$ | 0.002695 | 1.196021 |
| $\boldsymbol{\tilde{w}_t - w_t(h)}$ | 0.275188 | 1.932054** |
| ***R-squared*** | 0.079954 | |
| $\boldsymbol{adj. R^2}$ | 0.037750 | |
| $\boldsymbol{\hat{\sigma}}$ | 0.058081 | |
| ***Log likelihood*** | 167.1835 | |

*Note:* model is estimated using OLS with Newey-West corrected standard error. $\mathrm{adj. R}^2$ is the adjusted $\mathrm{R}^2$ . $\hat{\sigma}$ is the standard errors of regression. * and ** denote significant at the 5% and 10% level, respectively.

## Table III-3: Estimation results from the linear model –Australia

| Model 3<br>Asymmetric with smoothing, homogeneous coefficient with stock | | |
|---|---|---|
| ***Variable*** | ***Coefficient*** | ***t-Statistic*** |
| $\boldsymbol{c}$ | -0.027529 | -2.788905* |
| $\boldsymbol{\tilde{\pi}_t - \pi_t}$ | 0.149443 | 0.5226 |
| $\boldsymbol{\tilde{y}_t - y_t}$ | -0.180494 | -0.430482 |
| $\boldsymbol{\tilde{q}_t}$ | -0.068766 | -2.22509* |
| $\boldsymbol{\tilde{\imath}_{t-1} - i_{t-1}}$ | 1.14E-06 | 0.000529 |
| $\boldsymbol{\tilde{w}_t - w_t(S)}$ | 0.144411 | 2.91348* |
| ***R-squared*** | 0.0903 | |
| $\boldsymbol{adj.R^2}$ | 0.0547 | |
| $\boldsymbol{\hat{\sigma}}$ | 0.0583 | |
| ***Log likelihood*** | 193.664 | |

Note: model is estimated using OLS with Newey-West corrected standard error. $adj.R^2$ is the adjusted $R^2$ . $\hat{\sigma}$ is the standard errors of regression. * and ** denote significant at the 5% and 10% level, respectively.

# Appendix IV: Estimation of nonlinear models

**Table V-1: Estimation results from the nonlinear model (before adjustment) – Sweden**

| | *(1)* | *(2)* | *(3)* | *(4)* |
|---|---|---|---|---|
| ***Sample*** | ***80Q1:08Q4*** | ***80Q1:08Q4*** | ***80Q1:08Q4*** | ***80Q1:08Q4*** |
| ***Model*** | ***LSTR*** | ***LSTR*** | ***ESTR*** | ***LSTR*** |
| ***Transition variable ($s_t$)*** | $\pi_t - \widetilde{\pi}_t$ | $i_{t-1} - \tilde{i}_{t-1}$ | $w_t(h) - \widetilde{w}_t(h)$ | ***volatility*** |
| ***Linear part*** | ***0.040**** | | | |
| $\alpha_0$ | -0.035 | 0.011** | 0.005 | 0.012 |
| | (0.077) | (0.006) | (0.010) | (0.010) |
| $\beta_\pi$ | -1.942 | 0.317 | 1.271* | 0.771 |
| | (2.516) | (0.330) | (0.513) | (0.521) |
| $\beta_y$ | -1.008 | -0.912 | -0.588 | -0.144 |
| | (0.750) | (0.622) | (0.678) | (0.640) |
| $\beta_i$ | 0.006 | -0.002 | -0.013* | -0.015* |
| | (0.005) | (0.004) | (0.004) | (0.007) |
| $\beta_w$ | 0.358 | 0.502* | 0.389 | -0.667 |
| | (0.259) | (0.221) | (0.378) | (0.474) |
| $\beta_q$ | -0.049 | 0.025 | -0.141 | -0.114 |
| | (0.172) | (0.146) | (0.164) | (0.160) |
| ***Nonlinear part*** | | | | |
| $\alpha_0^*$ | 0.187 | -0.079* | -0.003 | -0.005 |
| | (0.247) | (0.028) | (0.026) | (0.014) |
| $\beta_\pi^*$ | -0.229 | -0.390 | -4.151* | -1.458* |
| | (1.223) | (0.758) | (2.352) | (0.665) |
| $\beta_y^*$ | 1.678 | 2.249* | 0.371 | -0.716 |
| | (1.535) | (1.066) | (1.376) | (0.878) |
| $\beta_i^*$ | -0.022* | 0.012* | 0.027* | 0.019* |
| | (0.011) | (0.004) | (0.013) | (0.007) |
| $\beta_w^*$ | -0.244 | -0. 934* | 0.232 | 1.010* |
| | (0.524) | (0.388) | (0.592) | (0.531) |
| $\beta_q^*$ | 0.310 | -0.077 | 0.123 | 0.521* |
| | (0.358) | (0.213) | (0.298) | (0.235) |
| ***Model parameters*** | | | | |
| $\gamma$ | 4.822 | 26.680 | 0.496 | 18.691 |
| $\gamma/\sigma_s\ (or\ \sigma_s^2)$ | 93.806 | 6.415 | 248.848 | 28064.351 |
| $c$ | 0.001* | 2.796* | 0.0128* | 0.0036* |
| | (0.000) | (0.000) | (0.000) | (0.000) |

*Note:* Table show coefficient of the variable over the entire sample period. Models are estimated by NLLS. The estimated standard errors are given in parentheses. $\gamma$ is the speed of transition between regimes. $\gamma/\sigma_s$ is the scaled speed for comparison across models. $c$ is the threshold value for particular transition variable.* and ** denote significant at the 5% and 10% level, respectively.

**Table V-2: Estimation results from the nonlinear model (before adjustment) – Sweden (continue)**

| | *(1)* | *(2)* | *(3)* | *(4)* |
|---|---|---|---|---|
| ***Sample*** | ***80Q1:08Q4*** | ***80Q1:08Q4*** | ***80Q1:08Q4*** | ***80Q1:08Q4*** |
| ***Model*** | ***LSTR*** | ***LSTR*** | ***ESTR*** | ***LSTR*** |
| ***Transition variable ($s_t$)*** | $\boldsymbol{\pi_t - \tilde{\pi}_t}$ | $\boldsymbol{i_{t-1} - \tilde{i}_{t-1}}$ | $\boldsymbol{w_t(h) - \tilde{w}_t(h)}$ | ***volatility*** |
| ***Summary statistics*** | | | | |
| $\boldsymbol{R^2}$ | 0.206 | 0.254 | 0.267 | 0.219 |
| $\boldsymbol{adj. R^2}$ | 0.102 | 0.156 | 0.171 | 0.117 |
| $\boldsymbol{SSR_{ratio}}$ | 0.862 | 0.810 | 0.795 | 0.846 |
| $\boldsymbol{\hat{\sigma}}$ | 0.057 | 0.055 | 0.053 | 0.056 |
| ***Log likelihood*** | 171.753 | 175.251 | 176.266 | 172.729 |

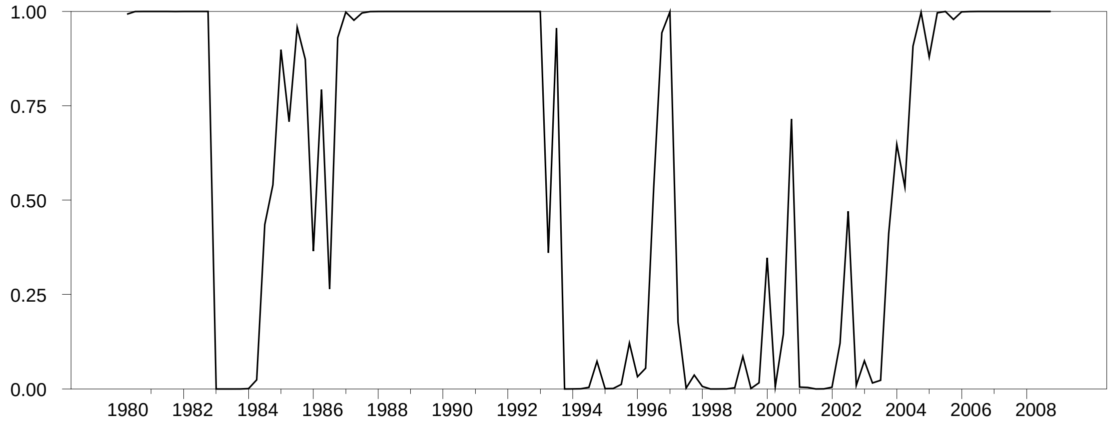
*Note:* $adj. R^2$ is the adjusted $R^2$ .$SSR_{ratio}$ denote sum of squared residuals ratio between the STR model and the linear specification. A lower ratio (i.e. less than one) indicates a better fit for the nonlinear model and vice versa. $\hat{\sigma}$ is the standard errors of regression. We prefer the regression model possessing higher values of $adj. R^2$, and log likelihood, but lower values of $SSR_{ratio}$ and $\hat{\sigma}$.

**Table V-3 P-values of diagnostic tests for STR models (before adjustment) - Sweden**

| | *(1)* | *(2)* | *(3)* | *(4)* |
|---|---|---|---|---|
| ***Sample*** | ***80Q1:08Q4*** | ***80Q1:08Q4*** | ***80Q1:08Q4*** | ***80Q1:08Q4*** |
| ***Model*** | ***LSTR*** | ***LSTR*** | ***ESTR*** | ***ESTR*** |
| ***Transition variable ($s_t$)*** | $\boldsymbol{\pi_t - \tilde{\pi}_t}$ | $\boldsymbol{i_{t-1} - \tilde{i}_{t-1}}$ | $\boldsymbol{w_t - \tilde{w}_t(h)}$ | ***volatility*** |
| ***Residual Tests*** | | | | |
| ***JB*** | 0.000* | 0.000* | 0.000* | 0.000* |
| ***ARCH-LM(1)*** | 0.161 | 0.410 | 0.291 | 0.486 |
| ***LM(1)*** | 0.415 | 0.695 | 0.379 | 0.664 |
| ***LM(4)*** | 0.240 | 0.792 | 0.388 | 0.897 |
| ***Remaining Nonlinearity*** | | | | |
| $\boldsymbol{\pi_t - \tilde{\pi}_t}$ | 0.991 | 0.391 | 0.959 | 0.959 |
| $\boldsymbol{y_t - \tilde{y}_t}$ | 0.259 | 0.216 | 0.976 | 0.297 |
| $\boldsymbol{i_{t-1} - \tilde{i}_{t-1}}$ | 0.310 | 0.975 | 0.904 | 0.677 |
| $\boldsymbol{w_t(h) - \tilde{w}_t(h)}$ | 0.614 | 0.638 | 0.919 | 0.909 |
| $\Delta\boldsymbol{\tilde{q}_t}$ | 0.962 | 0.791 | 0.158 | 0.462 |
| ***volatility*** | 0.232 | 0.651 | 0.890 | 0.330 |
| ***Parameter Constancy*** | | | | |
| $\boldsymbol{H_1}$ | 0.270 | 0.117 | 0.431 | 0.111 |
| $\boldsymbol{H_2}$ | 0.059** | 0.112 | 0.055** | 0.496 |
| $\boldsymbol{H_3}$ | 0.594 | 0.323 | 0.702 | 0.993 |

*Note:* numbers in this table are $p$-values. * and ** represent rejection of the null at the 5% and 10% significance levels, respectively. JB denotes the Jarque-Bera test for the null of normality of residuals. LM (1) and LM (4) denote LM tests for the null of no first and forth order serial correlation. ARCH-LM (1) denotes the null of no first order residual heteroskedasticity. For parameter constancy, rejection of either one of the null $H_1$, $H_2$ and $H_3$ will lead a conclusion favouring parameter non-constancy, otherwise the parameters are time-invariant.

**Figure V-1 Estimated transition function over time for Sweden**




*Note:* figure display the plots of the estimated logistic transition functions, $G(.)$, over time with exchange rate volatility as the transition variable. This is the graph before adding dummy variables.

**Table V-4 Estimation results from the nonlinear model (before adjustment) – Australia**

| | (1) | (2) | (3) |
|---|---|---|---|
| ***Sample*** | *75Q1:08Q4* | *75Q1:08Q4* | *75Q1:08Q4* |
| ***Model*** | *LSTR* | *LSTR* | *LSTR* |
| ***Transition variable*** ($s_t$) | $y_t - \tilde{y}_t$ | $i_{t-1} - \tilde{i}_{t-1}$ | $\tilde{q}_t$ |
| ***Linear part*** | ***0.778*** | | ***0.109*** |
| $\alpha_0$ | 0.002 | -0.020 | -0.114 |
| | (0.020) | (0.013) | (0.106) |
| $\beta_\pi$ | -0.036 | 0.271 | -0.716 |
| | (0.347) | (0.346) | (0.583) |
| $\beta_y$ | 0.507 | -0.497 | 1.009 |
| | (0.633) | (0.454) | (0.635) |
| $\beta_i$ | 0.001 | 0.004 | 0.008 |
| | (0.002) | (0.003) | (0.005) |
| $\beta_w$ | 0.084 | 0.200* | 0.043 |
| | (0.065) | (0.068) | (0.094) |
| $\beta_q$ | 0.003 | -0.021 | -0.213 |
| | (0.048) | (0.040) | (0.178) |
| ***Nonlinear part*** | | | |
| $\alpha_0^*$ | -0.117** | -0.149** | -0.029 |
| | (0.068) | (0.083) | (0.104) |
| $\beta_\pi^*$ | 2.069* | -0.783 | 3.395* |
| | (0.741) | (0.804) | (1.245) |
| $\beta_y^*$ | -2.762** | 3.160* | -4.038* |
| | (1.453) | (1.121) | (1.358) |
| $\beta_i^*$ | 0.005 | -0.020* | -0.012 |
| | (0.005) | (0.008) | (0.010) |
| $\beta_w^*$ | 0.149 | -0.244** | 0.362 |
| | (0.178) | (0.145) | (0.248) |
| $\beta_q^*$ | -0.267* | -0.843* | -0.816* |
| | (0.120) | (0.246) | (0.382) |
| ***Model parameters*** | | | |
| $\gamma$ | 4.640 | 6.681 | 2.518 |
| $\gamma/\sigma_s$ ($or$ $\sigma_s^2$) | 242.935 | 2.105 | 15.920 |
| $c$ | 0.011* | 4.369* | -0.191* |
| | (0.000) | (0.541) | (0.000) |

*Note:* Table show coefficient of the variable over the entire sample period. Models are estimated by NLLS. The estimated standard errors are given in parentheses. $\gamma$ is the speed of transition between regimes. $\gamma/\sigma_s$ is the scaled speed for comparison across models. $c$ is the threshold value for particular transition variable.* and ** denote significant at the 5% and 10% level, respectively.

**Table V-5 Estimation results from the nonlinear model (before adjustment) – Australia (continue)**

| | *(1)* | *(2)* | *(3)* |
|---|---|---|---|
| ***Sample*** | ***75Q1:08Q4*** | ***75Q1:08Q4*** | ***75Q1:08Q4*** |
| ***Model*** | ***LSTR*** | ***LSTR*** | ***LSTR*** |
| ***Transition variable ($s_t$)*** | $y_t - \tilde{y}_t$ | $i_{t-1} - \tilde{i}_{t-1}$ | $\tilde{q}_t$ |
| ***Summary statistics*** | | | |
| $R^2$ | 0.208 | 0.270 | 0.271 |
| $adj. R^2$ | 0.121 | 0.190 | 0.191 |
| $SSR_{ratio}$ | 0.869 | 0.819 | 0.800 |
| $\hat{\sigma}$ | 0.056 | 0.054 | 0.054 |
| ***Log likelihood*** | 199.075 | 204.445 | 204.525 |

*Note:* $adj. R^2$ is the adjusted $R^2$ .$SSR_{ratio}$ denote sum of squared residuals ratio between the STR model and the linear specification. A lower ratio (i.e. less than one) indicates a better fit for the nonlinear model and vice versa. $\hat{\sigma}$ is the standard errors of regression. We prefer the regression model possessing higher values of $adj. R^2$, and log likelihood, but lower values of $SSR_{ratio}$ and $\hat{\sigma}$.

**Table V-6 P-values of diagnostic tests for STR models - Australia**

| | *(1)* | *(2)* | *(3)* |
|---|---|---|---|
| ***Sample*** | ***75Q1:08Q4*** | ***75Q1:08Q4*** | ***75Q1:08Q4*** |
| ***Model*** | ***LSTR*** | ***LSTR*** | ***LSTR*** |
| ***Transition variable ($s_t$)*** | $y_t - \tilde{y}_t$ | $i_{t-1} - \tilde{i}_{t-1}$ | $\tilde{q}_t$ |
| ***Residual Tests*** | | | |
| ***JB*** | 0.000* | 0.000* | 0.000* |
| ***ARCH-LM(1)*** | 0.324 | 0.797 | 0.107 |
| ***LM(1)*** | 0.010* | 0.614 | 0.047* |
| ***LM(4)*** | 0.014* | 0.108 | 0.146 |
| ***Remaining Nonlinearity*** | | | |
| $\pi_t - \tilde{\pi}_t$ | 0.729 | 0.874 | 0.941 |
| $y_t - \tilde{y}_t$ | 0.996 | 0.367 | 0.164 |
| $i_{t-1} - \tilde{i}_{t-1}$ | 0.709 | 0.986 | 0.186 |
| $w_t(s) - \tilde{w}_t(s)$ | 0.695 | 0.456 | 0.922 |
| $\tilde{q}_t$ | 0.686 | 0.253 | 0.997 |
| ***volatility*** | 0.254 | 0.928 | 0.244 |
| ***Parameter Constancy*** | | | |
| $H_1$ | 0.997 | 0.927 | 0.095** |
| $H_2$ | 0.012* | 0.159 | 0.015* |
| $H_3$ | 0.857 | 0.417 | 0.279 |

*Note:* numbers in this table are $p$-values. * and ** represent rejection of the null at the 5% and 10% significance levels, respectively. JB denotes the Jarque-Bera test for the null of normality of residuals. LM (1) and LM (4) denote LM tests for the null of no first and forth order serial correlation. ARCH-LM (1) denotes the null of no first order residual heteroskedasticity. For parameter constancy, rejection of either one of the null $H_1$, $H_2$ and $H_3$ will lead a conclusion favouring parameter non-constancy, otherwise the parameters are time-invariant.